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# RTCNet: A Robust Hybrid Deep Learning Model for Soil Property Prediction Under Noisy Conditions

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**Abstract:** Accurate prediction of soil fertility and soil organic carbon (SOC) plays a critical role in precision agriculture and sustainable soil management. However, the high spatial-temporal variability inherent in soil properties, compounded by the prevalence of noisy data in real-world conditions, continues to pose significant modeling challenges. To address these issues, a robust hybrid deep learning model, termed RTCNet, was developed by integrating Recurrent Neural Networks (RNNs), Transformer architectures, and Convolutional Neural Networks (CNNs) into a unified predictive framework. Within RTCNet, a one-dimensional convolutional layer was employed for initial feature extraction, followed by MaxPooling for dimensionality reduction, while sequential dependencies were captured using RNN layers. A multi-head attention mechanism was embedded to enhance the representation of inter-variable relationships, thereby improving the model's ability to handle complex soil data patterns. RTCNet was benchmarked against two conventional models—Artificial Neural Network (ANN) optimized with a Genetic Algorithm (GA), and a Transformer-CNN hybrid model. Under noise-free conditions, RTCNet achieved the lowest Mean Squared Error (MSE) of 0.1032 and Mean Absolute Error (MAE) of 0.1852. Notably, under increasing noise levels, RTCNet consistently maintained stable performance, whereas the comparative models exhibited significant performance degradation. These findings underscore RTCNet's superior resilience and adaptability, affirming its utility in field-scale agricultural applications where sensor noise, data sparsity, and environmental fluctuations are prevalent. The demonstrated robustness and predictive accuracy of RTCNet position it as a valuable tool for optimizing nutrient management strategies, enhancing SOC monitoring, and supporting informed decision-making in sustainable farming systems.

**Keywords:** RTCNet; Soil fertility; CNN; Transformer; RNN; Sustainable agriculture; Precision agriculture

## 1 Introduction

Modern agriculture faces significant challenges due to the effects of climate change, soil degradation, and the need for increased food production. Soil fertility and SOC management are essential factors influencing agricultural productivity and sustainability. Accurate prediction of these soil properties is crucial for improving crop yield, optimizing fertilization, and enhancing soil management practices. However, predicting soil properties is a complex task due to the inherent variability of soils across different regions, as well as the temporal changes influenced by environmental conditions.

Traditional methods, such as multiple linear regression and principal component analysis (PCA), have been widely used for soil property prediction. However, these approaches often struggle to capture the nonlinear and dynamic relationships inherent in soil data. Recent advancements in machine learning and deep learning have opened new avenues [1] for improving prediction accuracy. RNNs, Transformer models, and CNNs have shown great promise in handling complex datasets with spatiotemporal dependencies. These models can learn from historical data and account for the dynamic nature of soil properties over time.

In this study, RTCNet, a hybrid deep learning model that integrates RNN, Transformer, and CNN-Long Short-Term Memory (LSTM) architectures, was introduced to predict key soil properties, such as SOC and fertility. By leveraging these advanced architectures, RTCNet was able to model complex interactions among soil variables more effectively.

Additionally, RTCNet incorporates dropout regularization, making it resilient to noisy data, which is often encountered in real-world agricultural datasets.

RTCNet's performance was compared with two baseline models: ANN + GA and Transformer + CNN. In ideal conditions, RTCNet delivered competitive performance in terms of prediction accuracy, achieving the lowest MSE and MAE. However, the true advantage of RTCNet lies in its robustness to noise. While traditional models, such as ANN + GA and Transformer + CNN, degraded significantly under noisy conditions, RTCNet maintained stable performance, making it particularly well-suited for real-world applications in agriculture.

Thus, RTCNet represents an important step in addressing the technical challenges of soil property prediction in agriculture. It bridges the gap between the need for accurate soil management and the technical limitations of current predictive models. By improving the robustness and accuracy of soil property prediction, RTCNet contributes to the broader goal of achieving sustainable and precision agriculture. Figure 1 shows a graphical summary of RTCNet's robustness.

The rest of the study is structured below. Section 2 reviews deep learning models for soil property prediction. Section 3 presents the soil properties and the dataset structure. Section 4 describes the basic RTCNet's architecture and its data processing pipeline. Section 5 evaluates the model's performance. Section 6 discusses the practical implications of RTCNet for soil management. Section 7 concludes the study and Section 8 discusses future work.

Recent literature on soil health using deep learning approaches can be organized into four main areas: analysis of soil properties, investigation of their impact on sustainability, application of machine learning and remote sensing, and the development of hybrid prediction models. These categories encompass both diagnostic and prognostic aspects of soil health.

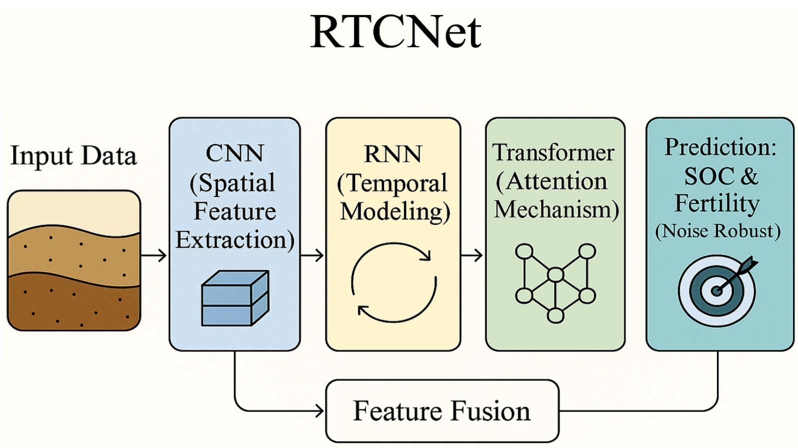


**Figure 1.** Graphical summary of RTCNet's robustness

## 2 Literature Review

Deep learning methods applied to soil health research can be divided into two main categories: diagnostic methods (analysis of current soil properties) and prognostic methods (prediction of future trends). Soil health is a critical factor for sustainable agriculture, as it determines the soil's ability to supply nutrients essential for crop production. This review focuses on scientific studies related to the detection, analysis, and prediction of soil properties, as well as decision-support tools for farmers and policymakers.

**a) Analysis and Assessment of Soil Properties**

Faustin et al. [2] provided a comparative analysis of soil properties across different agroforestry systems in Ivory Coast. The study uses robust statistical techniques, including analysis of variance (ANOVA) and Tukey tests, along with a Geographic Information System (GIS) for visualizing soil characteristics. While interactions between nutrients and their impact on fertility are well described, correlations between soil properties remain weak to moderate, limiting prediction accuracy. Moreover, the study focuses solely on physicochemical parameters, without considering microbiological aspects.

Swiderski et al. [3] conducted an extensive study on soil diversity and terrestrial microorganisms at the landscape scale using a digital mapping approach. Their research, part of the Perennial Observatory of the Environment (OPE) of ANDRA, spans a 240 $km^2$ area in Meuse and Haute-Marne. Using a systematic grid and repeated sampling campaigns, they characterized the physicochemical and microbiological properties of soils, providing insights into spatial distribution. Advanced geostatistical and regression methods, including principal component analysis (PCA) and boosted regression models, were employed. However, the study lacks integration of temporal variations, which limits the long-term applicability of the findings.

Ennaji et al. [4] presented a comprehensive review of machine learning (ML) applications in nutrient management, focusing on optimizing fertilization and improving agricultural productivity. The study highlights the rising adoption of ML models in modern agriculture for cost reduction, environmental protection, and enhanced nutrient evaluation. Despite its potential, the study also notes limitations, such as the need for large datasets, the complexity of interpreting ML models, and technological barriers in certain regions.

Chen et al. [5] introduced a method for assessing soil fertility quality (SFQI) based on geographically weighted principal component analysis (GWPCA). This method improves upon traditional PCA by accounting for spatial variations among soil fertility indicators, offering a more accurate large-scale evaluation. Sequential Gaussian Simulations (SGS) reduce spatial uncertainty. However, the approach depends heavily on sampling density and requires expert interpretation for parameter tuning.

Doran and Zeiss [6] emphasized soil health as a vital living system essential for productivity, ecosystem quality, and overall sustainability. They introduced a system of biotic and abiotic indicators to help land managers assess and monitor soil health. One limitation is the complexity of measuring biological indicators, which often demands specialized taxonomic knowledge. Moreover, while the study supports sustainable management practices, it offers limited guidance for large-scale implementation.

**b) Impacts of Soil Properties on Sustainability and Productivity**

Lal [7] discussed the role of soil carbon sequestration in mitigating climate change through the reduction of atmospheric $CO_2$ levels. Practices such as conservation tillage, cover cropping, and nutrient cycling can increase soil organic carbon (SOC), thereby enhancing soil health and food security. However, SOC sequestration has a finite potential and cannot fully offset long-term fossil fuel emissions. Other challenges include degradation, land misuse, and variability in sequestration efficiency.

Delgado and Gómez [8] emphasized the importance of physical, chemical, and biological properties in maintaining soil quality and productivity. Their work presents soil as a dynamic system influenced by interactions that affect water and air quality. While the study provides valuable insights into soil processes, it lacks predictive models for forecasting soil quality under various management practices.

Wenzel et al. [9] evaluated the use of the SOC:clay ratio as a universal indicator of soil health. Their findings suggest that SOC levels are more strongly influenced by amorphous aluminum oxyhydroxides $(\mathrm{Al}_0)$ and $\mathrm{CaCO}_3$ content than by clay. This challenges the validity of using a fixed threshold for evaluating soil health across diverse ecological zones. The regional focus on Lower Austria also limits the generalizability of results.

Khalil et al. [10] reviewed the impact of soil properties on the quality and growth of plant fibers. The study considers the interplay between nutrient availability, microbial activity, and soil structure. However, it lacks experimental validation and faces challenges in standardizing soil quality assessments across regions. The authors stress the need for interdisciplinary research to advance sustainable fiber production.

**c) Machine Learning and Remote Sensing for Soil Monitoring**

Ma et al. [11] examined the integration of soil science with machine learning models to predict soil properties from Visible and Near-Infrared (Vis-NIR) and Mid-Infrared (MIR) spectra. The use of Shapley values enhances interpretability by identifying important spectral bands. Although the approach improves prediction accuracy, it involves significant computational resources and depends on high-quality spectral data.

Diaz-Gonzalez et al. [12] applied machine learning and remote sensing to estimate soil quality indicators from large datasets. While effective for improving productivity and soil management, these models often lack scalability to small and medium farms due to technical complexity and infrastructure requirements.

Dvorakova et al. [13] improved the prediction of SOC using Sentinel-2 satellite imagery. By developing a reflectance composite method and using PLSR with bootstrapping, they reduced uncertainty in SOC estimates. However, the method depends on optimal soil exposure conditions, making it vulnerable to vegetation cover, cloudiness, and seasonal changes.

Sahbeni et al. [14] explored the use of remote sensing for mapping soil salinity, a key environmental issue affecting food production. While remote sensing shows great potential for large-scale assessments, limitations include spatial resolution, temporal frequency, data cost, and accuracy requirements. The study calls for interdisciplinary collaboration to enhance monitoring capabilities.

**d) Deep Learning Models for Soil Property Prediction**

Recent research has increasingly demonstrated the effectiveness of hybrid deep learning models in predicting soil properties by integrating diverse data sources such as optical satellite images, climatic data, and soil samples ([15–17]). These models, including hybrid Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), have shown superior accuracy in predicting both physical and chemical soil properties, often resulting in lower root mean-squared error (RMSE) compared to traditional regression techniques.

For example, Datta and others have successfully used hyperspectral data in combination with deep learning frameworks such as Long Short-Term Memory Networks (LSTM) to efficiently assess soil attributes like organic carbon and pH. These innovations are paving the way for more precise agricultural practices and sustainable land management strategies. Several recent studies illustrate these advancements:

- Cao et al. [18] developed a hybrid Transformer-CNN model using Vis–NIR data from the LUCAS database. This model outperforms conventional methods in predicting soil properties such as pH, clay, and organic carbon, though it remains computationally intensive and needs adaptation to diverse soil environments.
- Shahabi et al. [19] proposed a hybrid ANN-GA model (MM-GANN) for predicting cation-exchange capacity (CEC). While the model improves accuracy, it relies heavily on high-quality input data and suffers from interpretability challenges for non-experts. Its application was validated only in the Tabriz plain (Iran), suggesting the need for broader testing.
- Kakhani et al. [20] introduced SSL-SoilNet, a Transformer-based framework that uses self-supervised contrastive learning to predict soil organic carbon (SOC) at a large scale. It combines Vision Transformers (ViT) for image data with Transformers for climate data, outperforming conventional ML models. However, it faces challenges related to data quality, model complexity, and generalization across varying soil and climate conditions.
- Ng et al. [21] specifically investigated how training sample size affects the performance of CNNs versus traditional models like PLSR and Cubist using VIS–NIR–SWIR spectra. The study found that CNNs outperform traditional models when the number of samples exceeds 1500–1800, with optimal performance observed above 2000 samples. It also contributes learning curves and a sensitivity analysis to better interpret CNN predictions.

While the aforementioned models, such as the Transformer-CNN and hybrid ANN-GA approaches, have demonstrated impressive performance in soil property prediction, they often rely heavily on high-quality input data, which can limit their applicability in real-world scenarios where data might be noisy or incomplete. In contrast, the RTCNet model proposed in this study addresses these challenges by being inherently robust to noise. Its ability to function effectively with lower-quality data makes it a promising solution for large-scale soil monitoring, particularly in regions where high-quality data may be difficult to obtain.

## 3 Soil Property Datasets

Several datasets were used to study soil properties, particularly in areas such as precision agriculture, geology, and environmental management. These datasets provide valuable insights into soil characteristics, supporting the development of more effective predictive models and decision-support tools for sustainable soil management.

**a) Obtaining soil properties with the US National Cooperative Soil Survey (NCSS)**

NCSS [22] collects soil data on a global scale using a combination of laboratory surveys, international collaborations, and advanced technologies. In addition to direct measurements, NCSS uses remote sensing technologies, particularly infrared sensors such as those used in Near-Infrared (NIR) spectroscopy, to estimate certain physico-chemical properties of soils, such as moisture and organic matter content. These sensors provide rapid, non-invasive data that is useful for soil mapping and large-scale environmental studies.

**Table 1.** Soil texture and composition data

| Reference | Depth (cm) | Field Texture | Clay (%) | Lime (%) | Sand (%) |
|---|---|---|---|---|---|
| 81P03751 | 18 | EPA | 4.40 | 19.60 | 76 |
| 81P03752 | 150 | FLS | 19.10 | 21 | 59.90 |
| 81P03753 | 40 | C | 54.30 | 29.30 | 16.40 |
| 81P03754 | 90 | C | 47.20 | 30.80 | 22 |
| 81P03755 | 15 | SCL | 22.50 | 25.40 | 52.10 |
| 81P03756 | 70 | SCL | 20 | 25.20 | 54.80 |
| 81P03757 | 10 | FLS | 16.80 | 27.30 | 55.90 |
| 81P03758 | 20 | FLS | 13.30 | 28.70 | 58 |

**Table 2.** Chemical properties of soil

| Reference | Bulk Density ( $g/cm^3$) | Organic Carbon (%) | pH(KCD) | pH ($H_2O$) | Base Saturation (%) | Humidity (%) |
|---|---|---|---|---|---|---|
| 81P03751 | 1.00 | 0.45 | 4.10 | 4.20 | 57 | 23.28 |
| 81P03752 | 1.01 | 0.19 | 3.70 | 4.20 | 42 | 27.83 |
| 81P03753 | 1.06 | 0.72 | 5.20 | 6.10 | 8 | 39.22 |
| 81P03754 | 1.06 | 0.70 | 5.80 | 6.60 | 11 | 37.24 |
| 81P03755 | 1.02 | 0.26 | 3.80 | 4.30 | 34 | 29.29 |
| 81P03756 | 1.01 | 0.33 | 4.60 | 5.20 | 34 | 28.52 |
| 81P03757 | 1.02 | 2.00 | 5.20 | 5.60 | 37 | 27.77 |
| 81P03758 | 1.01 | 1.75 | 5.10 | 5.40 | 35 | 26.86 |

**Table 3.** Nitrogen, potassium, phosphorus and soil fertility

| Reference | Azote (%) | Potassium (%) | Phosphore (ppm) | Organic Matter (%) | Organic Biomass (%) | Fertility |
|---|---|---|---|---|---|---|
| 81P03751 | 0.02 | 0.28 | 4.24 | 0.77 | 0.23 | Fertile |
| 81P03752 | 0.01 | 0.59 | 4.91 | 0.33 | 0.10 | Fertile |
| 81P03753 | 0.04 | 1.38 | 6.25 | 1.24 | 0.37 | Not very fertile |
| 81P03754 | 0.04 | 1.25 | 5.82 | 1.20 | 0.36 | Not very fertile |
| 81P03755 | 0.01 | 0.70 | 4.86 | 0.45 | 0.13 | Fertile |
| 81P03756 | 0.02 | 0.65 | 4.74 | 0.57 | 0.17 | Fertile |
| 81P03757 | 0.10 | 0.61 | 4.48 | 3.44 | 1.03 | Fertile |
| 81P03758 | 0.09 | 0.55 | 4.23 | 3.01 | 0.90 | Fertile |

However, for more precise analyses, such as exact mineral composition, laboratory surveys are still essential. The combined approach of in-situ measurements and remote sensing provides a comprehensive and detailed assessment of soils. By way of illustration, soil properties in the Senegal region, such as texture (proportions of clay, silt, and sand), bulk density, organic carbon, pH, as well as nitrogen, potassium, and phosphorus levels, are listed in Table 1, Table 2, and Table 3. Each data reference corresponds to a specific pedon or chart unit.

The table containing the NCSS soil characterization report for Senegal was vertically split to obtain these three tables. The data obtained via NCSS does not allow rapid soil dynamics (such as seasonal changes or changes linked to recent agricultural practices) to be monitored, compared with real-time remote sensing data such as that offered by Sentinel-2. Nor can the NCSS capture very fine changes at a local scale.

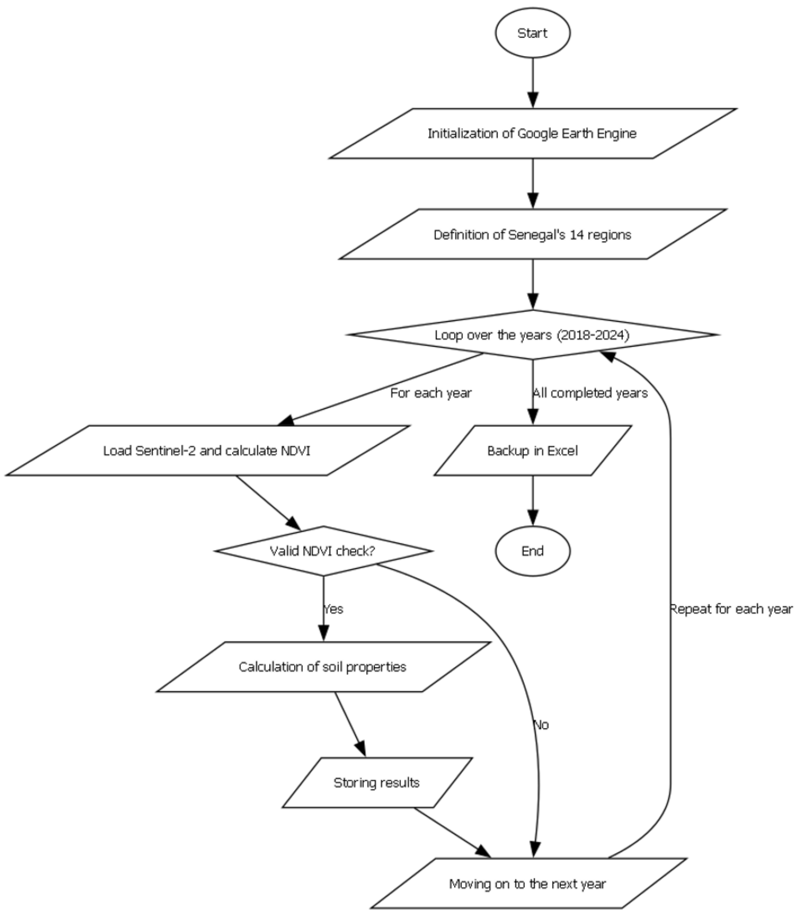


**Figure 2.** Calculating soil properties

**b) Obtaining soil properties using remote sensing in Senegal**

The Copernicus program's Sentinel-2 satellite can be used to analyze a number of soil parameters that are essential for soil management in Senegal, including pH, nitrogen and potassium content, moisture, plant and organic biomass, and SOC stock. Thanks to its 13 spectral bands covering the Vis-NIR, and short-wave infrared (SWIR), it is possible to obtain information on soil fertility, its level of degradation, salinity, and texture. Soil analysis can also be used to determine which crops are best suited to a given region, based on the chemical composition and moisture content of the soil. These values were estimated from radiometric indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), or Bare Soil Index (BSI) and can be predicted using deep neural models trained on a rigorous dataset containing these parameters.

**c) Soil properties obtained by analyzing Sentinel-2 images (COPERNICUS/S2)**

NDVI was calculated from the Sentinel-2 image collection (COPERNICUS/S2), which provides spectral bands including the red band (B4) and the NIR band (B8). The NDVI is defined by the formula:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

where, $NIR$ and $RED$ are the values of the B8 and B4 bands, respectively. Once NDVI is extracted for each region and year (2018-2024), soil properties can be estimated using empirical relationships, where each soil parameter (pH, clay content, organic matter, nitrogen, phosphorus, potassium, SOC, organic biomass, and fertility) is derived linearly from NDVI.

Based on these values, a suitable crop type was assigned according to NDVI. The final dataset was an Excel file containing NDVI values and soil properties for the 14 regions of Senegal over the period 2018-2024, with their corresponding latitude and longitude. The process of obtaining the data is summarized in Figure 2.

## 4 Proposed RTCNet Model

A hybrid model combining an RNN, a Transformer with attention mechanism and a CNN-LSTM offers a complete capture of local and global dependencies, while ensuring efficient management of long relationships thanks to attention. It enables better generalization and robustness, reducing the risk of overfitting and improving performance on varied data. In addition, it compensates for the computational limitations of Transformers by efficiently structuring and pre-processing data via CNN and LSTM. Therefore, it was adopted for the prediction of soil properties.

**a) RTCNet hybrid model architecture**

The RTCNet hybrid architecture effectively combines convolutional, recurrent and attentional layers to capture both local and global relationships in sequential data. The model starts with an input layer that supports sequences of length 14 with a single feature per sample, i.e., an input tensor of the form (16,14,1), where 16 is the batch size or number of sequences before the model updates its parameters, 14 is the sequence length, and 1 is the number of features per sample. The first block of the model is a CNN block, which starts with a Conv1D layer with 64 filters and a kernel of size 2, making it possible to extract local features from the sequences. This layer is followed by a MaxPooling1D layer (pool size = 2), which reduces dimensionality while preserving essential information. The model then includes an RNN block. A first SimpleRNN layer (64 units, ReLU activation) is used to capture short-term temporal dependencies in the sequence. A second SimpleRNN layer refines sequence learning and provides a better understanding of long-term relationships.

In parallel, the model uses a MultiHeadAttention layer (4 attention heads, key dimension = 64) to extract complex relationships between elements in the sequence. A GlobalAveragePooling1D layer is applied to summarize the information captured by the attention. The output from the two blocks (RNN and Transformer) is then merged via a Concatenate layer. This step combines the information extracted by the two blocks and creates a richer representation of the sequence.

Finally, a Dense layer with 64 units and ReLU activation performs a non-linear transformation before the final output. The output layer is a Dense layer with 3 units and linear activation, producing the final predictions for the three targets: SOC, plant biomass, and fertility.

This hybrid architecture makes it possible to exploit local dependencies captured by CNNs, temporal dependencies learned by RNNs and complex relationships extracted by attention, thereby improving performance for sequential classification and prediction tasks. The table corresponding to this architecture is shown in Table 4.

The architectural choices made in the RTCNet-Hybrid model were designed to strike a balance between complexity, efficiency, and the ability to capture complex spatiotemporal patterns in soil data. The choice of 64 units for each recurrent (RNN) and fully connected (Dense) layer was influenced by empirical results and best practices in the literature. Specifically, 64 units provide sufficient capacity to capture meaningful representations of the data without leading to excessive computational demands. This size is commonly used in deep learning architectures, particularly for problems involving sequence data and time-series predictions, where the model must capture intricate temporal dependencies while avoiding overfitting.

The decision to use two SimpleRNN layers with 64 units each allows the model to learn sequential dependencies at different levels of abstraction. The first SimpleRNN layer captures temporal relationships at the sequence level, while the second one, connected after the first, refines these learned representations by processing the output further. Additionally, the inclusion of a MultiHeadAttention layer with four attention heads allows the model to attend to

**Table 4.** Architecture of the RTCNet hybrid model

| Layer (type) | Output Shape | Param # | Connected to |
|---|---|---|---|
| InputLaver (Input) | (None, 14, 1) | 0 | - |
| ConvlD (64 filters, kemel=2) | (None, 14, 64) | 192 | InputLayer |
| MaxPoolinglD (pool=2) | (None, 7, 64) | 0 | Conv1D |
| SmpleRNN (64 units) | (None, 1, 64) | 8,256 | MaxPoolinglD |
| MulthHeadAittention (4 heads) | (None, 7, 64) | 66,368 | MaxPooling1D |
| SmpleRNN (64 units) | (None, 64) | 8,256 | SimpleRNN |
| GlobalAveragePooling1D | (None, 64) | 0 | MultiHeadAttention |
| Concatenate | (None, 128) | 0 | SimpleRNN, GlobalAveragePooling1D |
| Dense (64 units, ReLU) | (None, 64) | 8,256 | Concatenate |
| Dense (3 units, Linear) | (None, 3) | 195 | Dense |

different parts of the input sequence simultaneously, facilitating a better understanding of long-range dependencies and correlations across time.

The GlobalAveragePooling1D layer helps reduce the dimensionality of the feature space, summarizing the temporal information across the sequence into a fixed-length vector, which is essential for efficient processing in downstream layers. The Concatenate layer combines the outputs of the SimpleRNN and MultiHeadAttention, effectively merging both sequential and attention-based features, enriching the model's representation of the data.

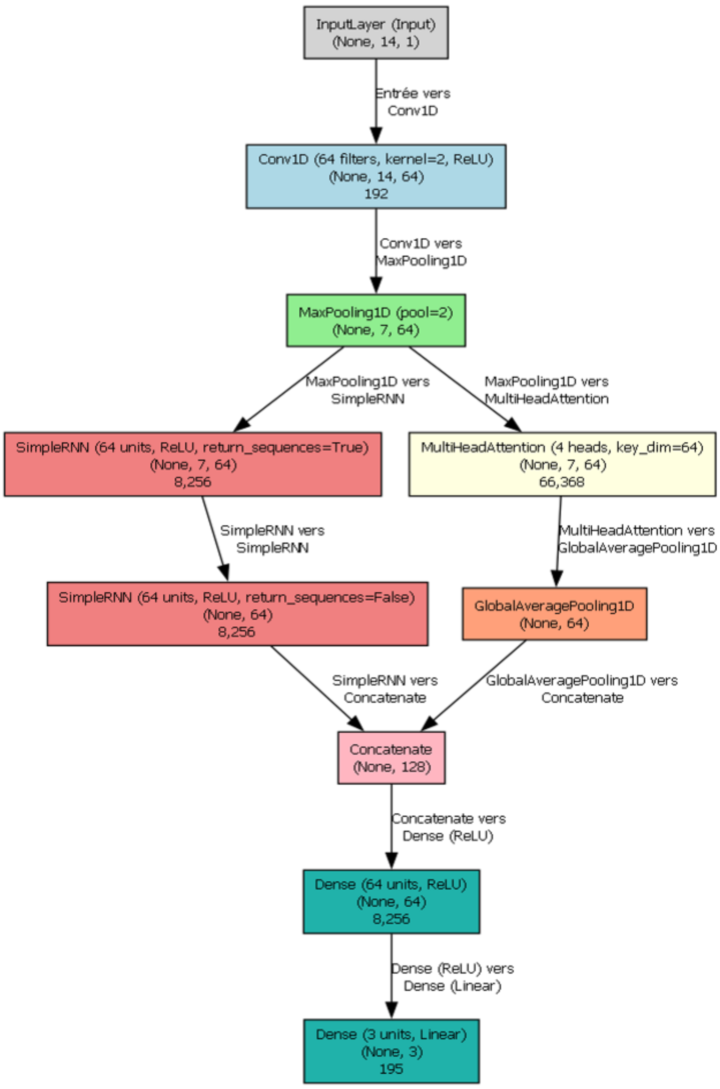


**Figure 3.** Architecture of the RTCNet

The Dense layers with 64 units allow for a non-linear transformation of the concatenated features, further refining the model's understanding of the soil properties. The final Dense layer with three units produces the model's output, representing the predicted soil properties (e.g., SOC, pH, and fertility), with a linear activation function ensuring that the output is continuous and suitable for regression tasks.

Overall, the architectural choices were made to enable RTCNet to capture both local and long-range dependencies in the data, while also providing enough capacity to model the complex interactions among the various soil properties. The number of layers and units was chosen based on the need for sufficient representation power while maintaining computational efficiency. Figure 3 shows the RTCNet architecture.

**b) Processing flow of the RTCNet hybrid model**

The RTCNet hybrid model's processing flow begins by embedding data in the input layer (InputLayer), which accepts data in the form [batch size, 14, 1], where 14 is the number of features per sequence and 1 is the feature size. Next, a Conv1D layer with 64 filters and a kernel of size 2 is applied to extract local features from the time series, producing a tensor of the form [batch size, 14, 64]. A MaxPooling1D layer with a pool factor of 2 is then used to reduce the dimensionality of the sequence while retaining essential information, resulting in a tensor of shape [batch size, 7, 64]. Next, the first layer SimpleRNN with 64 units is applied to learn local temporal dependencies, generating an output of the form [batch size, 7, 64]. After this, the second layer SimpleRNN, without sequence feedback, produces an output of the form [batch size, 64]. In parallel, a MultiHeadAttention layer with 4 heads learns the global relations of the sequence, generating a tensor of form [batch size, 7, 64], which is then processed by a GlobalAveragePooling1D layer to reduce the time dimension to [batch size, 64]. The outputs of the second layer SimpleRNN and the GlobalAveragePooling1D are merged to create a vector of size [batch size, 128], which is then projected into a higher dimensional space via a layer Dense with 64 units, producing a tensor of shape [batch size, 64]. The final layer Dense with three units and linear activation generates the three yield predictions, producing a tensor of form [batch size, 3], where each element of the output corresponds to the predicted values for the three targets: SOC, plant biomass and fertility.

**c) Comparison of the proposed model with recent hybrid models**

The proposed architecture was compared with two hybrid models cited in the state of the art in Table 5. The ANN + GA model offers improved prediction accuracy but suffers from high complexity and limited scalability. The Transformer + CNN model achieves high accuracy, particularly in soil property prediction, though it faces challenges in computational complexity and optimization. Lastly, the RTCNet model utilizes CNN, SimpleRNN, and Transformer, capturing spatial, sequential, and contextual features, with the main challenge being the need for optimization across different datasets.

**Table 5.** Comparison of hybrid deep learning models

| Model | Components | Advantages | Challenges |
|---|---|---|---|
| ANN + GA [23] | ANN and GA | Improved prediction accuracy | High complexity and limited scalability |
| Transformer + CNN [24] | Transformer and CNN | High accuracy in soil property prediction | Computational complexity and optimization issues |
| Proposed RTCNet | CNN, SimpleRNN and Transformer | Captures spatial, sequential, and contextual features | Requires optimization for different datasets |

**d) Processing dataset data**

The dataset used initially consisted of ten columns. This dataset contained two columns, region and adapted culture, which need to be converted into numbers to train the models. The data pre-processing phase began with the mapping of categorical values into numerical variables. In particular, the region column of the dataset contains text values representing different regions of Senegal. To transform these values into integers, a mapping was performed, where each region was associated with a unique number. For example, the Dakar region was mapped to number 1, Thies to number 2, and so on for all the regions in the dataset. Next, the OneHotEncoding method was used to encode the categorical variable adapted culture. This method transformed each category in the adapted culture column into a series of binary columns. If a row belongs to a given culture, the corresponding column will take on the value 1, otherwise it will take on the value 0. This makes it possible to convert a categorical variable into several binary variables, which is crucial if machine learning models are to be able to process this data efficiently. Four crop categories, namely groundnuts, millet, cowpeas and rice, were chosen in the dataset. Therefore, the adapted crop column became four columns after the OneHotEncoding encoding, ending up with 14 characteristics or attributes in the dataset.

Data normalization was then applied to the input variables. This reduces bias caused by the different scales of the variables. A StandardScaler was used to center the data around 0 and rescale it so that each feature has a mean of 0 and a standard deviation of 1. This step is crucial to ensure that the model can learn optimally without being influenced by the scale of the different features. Finally, the data was reformatted into tensors of the form (batch size, features, 1) before being fed into the models. The input data was thus restructured to fit the deep neural models.

Tensors are multi-dimensional data structures that pass through the different layers of the model as they are trained. The models were trained over 50 epochs with a batch size of 16. Each input to the models has 16 samples (or batches, batch size) with a sequence of length 14, and each element of the sequence has a single characteristic (the dimension of 1). Each input is a tensor T of the form (16, 14, 1) and corresponds to a batch of 16 samples, with 14 features per sample, and each feature is represented by a single channel (hence 1). This format allows the model to exploit the temporal and spatial relationships between the different features. Below is an illustration of the format of the main input tensor in the models before the start of training.

The tensor has the shape (16,14,1) and can be illustrated in Figure 4.

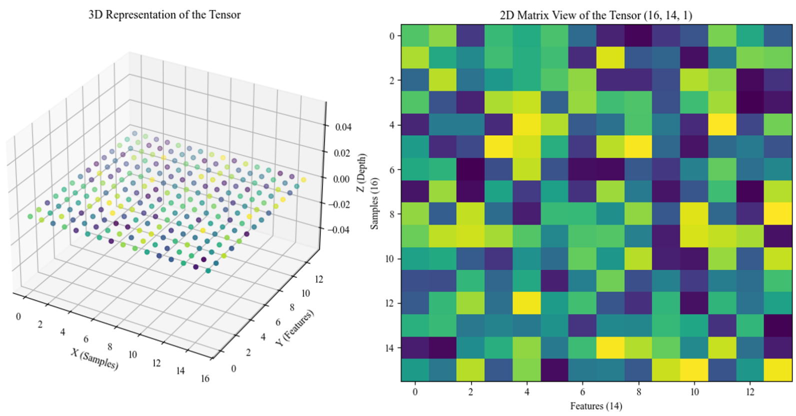


**Figure 4.** Tensor entered in each model at the start of training

On the tensor, the data are centred around 0 with a standard deviation of 1 due to normalization. The input tensor in the models therefore has the form (16, 14, 1), where 16 represents the number of examples in the batch, 14 is the number of input features (10 initial features plus 4 new columns after encoding the “adapted culture” column) and 1 indicates the time dimension (sequence of length 1).

e) Tensor flow and RTCNet model training

When training the RTCNet model, the parameters (connection weights) were adjusted to minimize the loss function (loss). If the loss decreases progressively over time, this indicates that the model is learning to better predict the outputs corresponding to the inputs. Convergence is reached when the loss stops decreasing significantly, indicating that the model has found a set of parameters that sufficiently minimizes the error.

The RTCNet model is a hybrid architecture combining CNN, RNN and an attention mechanism. The input tensor of form (16, 14, 1) represents a batch of 16 sequences, each composed of 14 time steps with a single feature per time step.

Data processing in RTCNet follows several steps:

**Step 1: Input (InputLayer):** The input to the model is a shape tensor (16, 14, 1), which is routed directly to the various branches of the hybrid architecture.

**Step 2: Bloc CNN**

- Conv1D (64 filters, kernel=2) : A layer Conv1D applies 64 filters of size 2, producing an output of the form (16, 14, 64).
- MaxPooling1D (pool=2) : A layer of MaxPooling1D reduces the sequence by applying a pooling of size 2, generating a tensor of shape (16, 7, 64).
- Bloc RNN:
  * SimpleRNN (64 units, return sequences=True): This layer takes an input of the form (16, 7, 64) and produces a tensor of the form (16, 7, 64), preserving the temporal dimension.

**Step 3: Bloc transformer**

- MultiHeadAttention (4 heads) : A layer MultiHeadAttention captures the global relations in the sequence and returns a tensor of form (16, 7, 64).

**Step 4: Merging and aggregating**

- GlobalAveragePooling1D: Each output of the RNN and Transformer blocks passes through a layer of GlobalAveragePooling1D, reducing the tensors to the form (16, 64).

- Concatenation of outputs: The two tensors (16, 64) from the RNN and Transform blocks are concatenated to form a tensor of form (16, 128).

**Step 5: Final classification**

- Dense (64 units, ReLU) : A layer Dense with ReLU activation transforms the tensor into (16, 64).
- Dense (3 units, Linear): A final layer Dense with three units generates the final output of the shape model (16, 3).

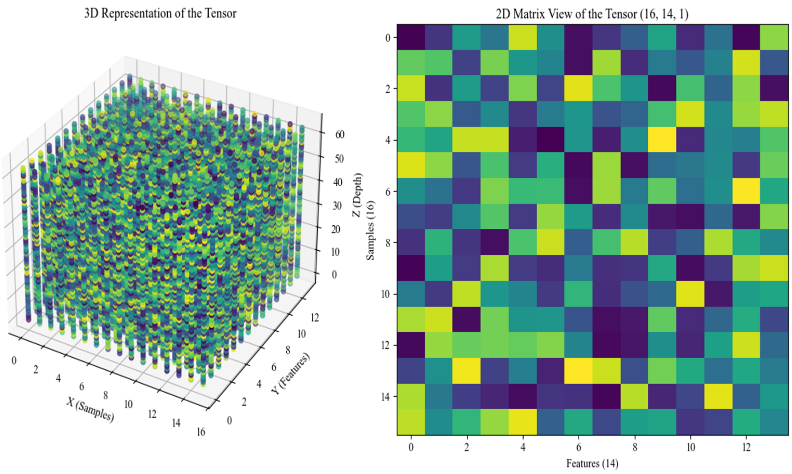


**Figure 5.** Output of the Conv1D layer

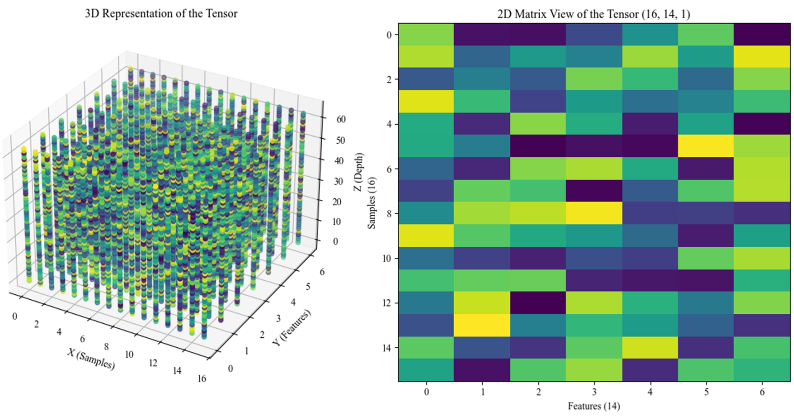


**Figure 6.** Output of the MaxPooling1D layer

Thus, the tensor (16, 14, 1) passes through the various layers of the RTCNet model to produce an output of the form (16, 3). Figures 5-11 illustrate the sequential processing flow within RTCNet, showcasing the outputs of key layers including Conv1D, MaxPooling1D, RNN and Transformer concatenation, and Dense layers, along with their corresponding tensor shapes and the overall model architecture.

In RTCNet, the output (16, 3) corresponds to the three targets to be predicted:

- SOC: Predicting and managing SOC is essential for improving soil quality while reducing the ecological footprint of agricultural practices.
- Vegetable biomass: A good indicator of soil health. Soils rich in biomass are often more fertile and resistant to extreme climatic conditions.
- Fertility: Optimizes farming practices by adjusting inputs (fertilizers and soil improvers) and planning harvests according to soil characteristics.

## 5 Results

### 5.1 Simulation Environment

To evaluate the performance of the proposed model, all experiments were conducted on a system with the following specifications:

- **Operating system:** Windows 10 (Version 10.0.26100)

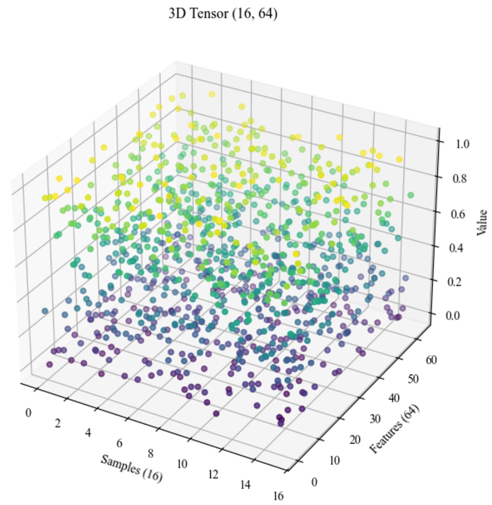


**Figure 7.** Tensor (16, 64)

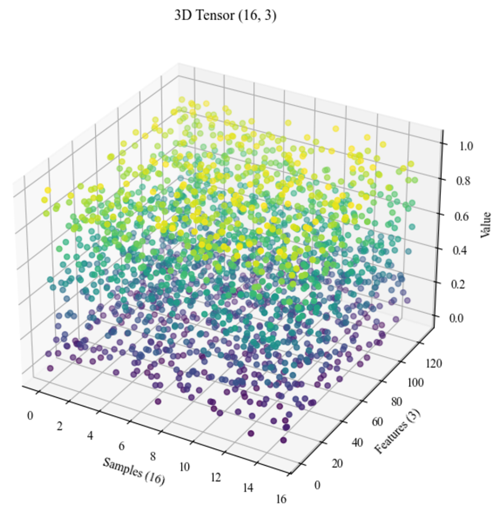


**Figure 8.** Output concatenation of RNN and Transformer

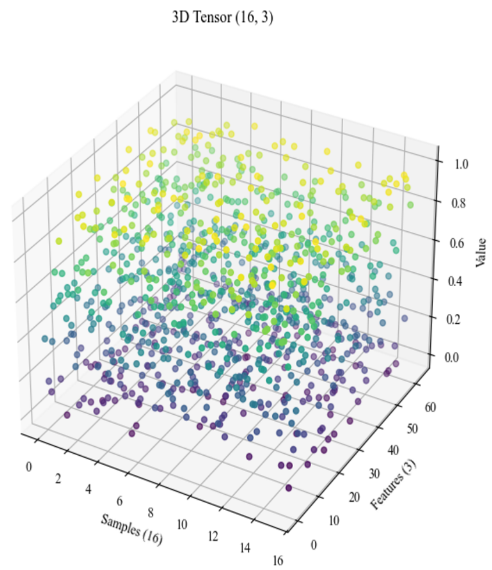


**Figure 9.** Output of the Dense layer

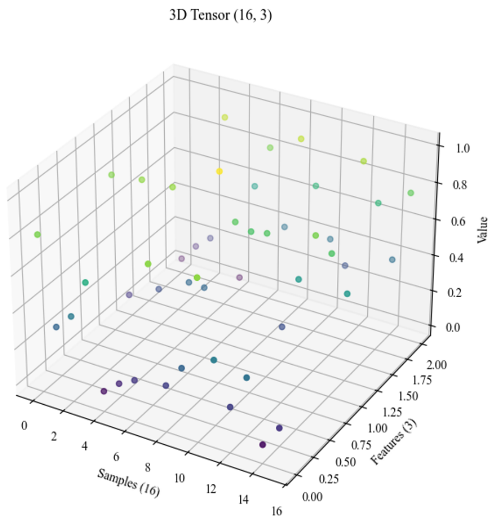


**Figure 10.** Tensor (16, 3)

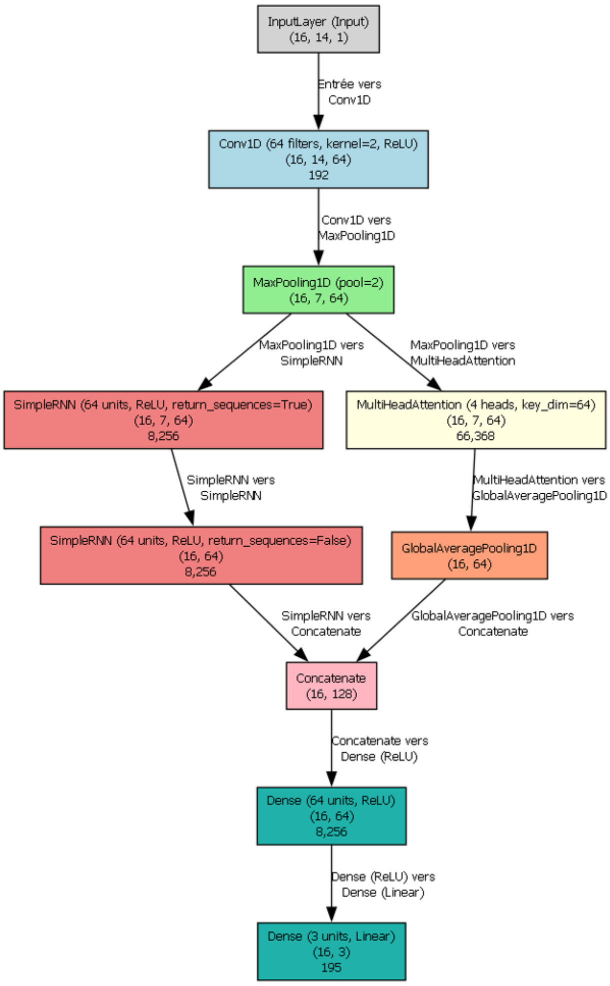


**Figure 11.** Tensor flow diagram in RTCNet

- **Machine name:** DESKTOP-PEAG
- **Processor:** Intel 64-bit, Family 6, Model 154, Stepping 4 (GenuineIntel)
- **Physical cores:** 10
- **Logical cores:** 12
- **CPU frequency:** 1.3 GHz

### 5.2 Simulation

To compare the RTCNet, Transformer+CNN, ANN+GAN and CNN-LSTM models, and measure the impact of ablations on the RTCNet, MSE, MAE, training time and number of parameters are crucial. MSE and MAE measure the accuracy of predictions, with MSE being more sensitive to large errors and MAE being more robust to outliers. Training time assesses the efficiency of each model in terms of computational resources. The number of parameters assesses the complexity and generalizability of each model. When noise is added to the data, these criteria can be used to analyze the robustness of the models to external disturbances, ensuring a fair comparison in terms of performance and resources. RTCNet ablation was used to assess the impact of each sub-model on RTCNet performance. In all simulations, 80% of the input data was used for training and 20% for model testing.

a) RTCNet model performance without optimization

To evaluate the effectiveness of the proposed RTCNet architecture, its performance was compared against several baseline models under both clean and noisy conditions. Gaussian noise was generated from a normal distribution with zero mean and a standard deviation defined by the noise_factor parameter. This noise was added element-wise to the input data to simulate random perturbations. The addition preserved the original shape of the data. Finally, the noisy values were clipped between 0 and 1 to remain within a valid range. Furthermore, an ablation study was conducted to assess the contribution of each major component within RTCNet (CNN, RNN, and Transformer branches). Table 6, Table 7, and Table 8 summarize the results.

**Table 6.** Performance comparison without Gaussian noise

| Model | MSE | MAE | Time (s) | Parameters |
|---|---|---|---|---|
| ANN + GA | 0.1017 | 0.1847 | 89.97 | 10,371 |
| CNN-LSTM | 0.1038 | 0.1856 | 359.46 | 43,545 |
| Transformer + CNN | **0.1010** | **0.1845** | 301.49 | 66,755 |
| RTCNet | 0.1032 | 0.1852 | **394.24** | **121,155** |

**Table 7.** Performance comparison with Gaussian noise

| Model | MSE | MAE | Time (s) | Parameters |
|---|---|---|---|---|
| ANN + GA | 0.1036 | 0.1863 | 71.69 | 10,371 |
| CNN-LSTM | 0.1267 | 0.2048 | 352.91 | 43,545 |
| Transformer + CNN | **0.1016** | **0.1848** | 265.69 | 66,755 |
| RTCNet | 0.1063 | 0.1878 | **389.98** | **121,155** |

**Table 8.** Ablation study on RTCNet components

| Model Variant | MSE | MAE | Time (s) | Parameters |
|---|---|---|---|---|
| RTCNet - No CNN | **0.1015** | **0.1840** | 414.34 | 18,692 |
| RTCNet - No RNN | 0.1020 | 0.1856 | 456.81 | 75,139 |
| RTCNet - No Transformer | 0.1013 | 0.1843 | **368.35** | **25,155** |

The results indicate that while the RTCNet model has a slightly higher number of parameters and computational time compared to the other models, it maintains competitive performance, particularly in the presence of noise. The ablation study confirms that each of the models embedded in RTCNet (CNN, RNN, and Transformer) contributes significantly to the overall performance. However, removing CNN improves the RTCNet model and slightly places it above the Transformer + CNN model.

b) RTCNet performance with dropout regularization

To evaluate the effect of architectural enhancements on RTCNet,d an optimized version of the model—RTCNet Optimized, was introduced. This version incorporates deeper convolutional layers, two Transformer blocks with residual connections and dropout regularization, and a more robust fusion mechanism.

The table compares the performance of all models, including both the standard RTCNet and RTCNet Optimized, under Gaussian noise conditions. The evaluation metrics include MSE, MAE, training time, and total number of parameters.

As shown in Table 9, the optimized version of RTCNet demonstrates consistent improvements in MSE and MAE under both noisy and noise-free scenarios. Although it requires significantly more parameters and longer training time, it outperforms the original RTCNet in terms of predictive accuracy. Notably, the optimized model exhibits resilience to Gaussian noise, as MSE slightly decreases from 0.1037 to 0.1031 when noise is added. This suggests a better generalization capacity and robustness of RTCNet_Optimized, likely due to the deeper architecture and enhanced attention mechanisms.

c) Performance of the pruned RTCNet model

This subsection presents the performance of the RTCNet model optimized with pruning during the training and testing phases. Pruning is a model compression technique that involves removing the least significant weights from the neural network layers, thereby reducing the model size while preserving its performance. The results obtained during training and testing are summarized in Table 10.

**Table 9.** Performance comparison with Gaussian noise

| Model | MSE | MAE | Time (s) | Parameters |
|---|---|---|---|---|
| ANN + GA | 0.1036 | 0.1863 | 71.69 | 10,371 |
| CNN-LSTM | 0.1267 | 0.2048 | 352.91 | 43,545 |
| Transformer + CNN | **0.1016** | **0.1848** | 265.69 | 66,755 |
| RTCNet | 0.1063 | 0.1878 | **389.98** | **121,155** |
| RTCNet_Optimized | 0.1031 | 0.1855 | 566.49 | 187,843 |

**Table 10.** MSE and MAE during training and testing for the pruned RTCNet model

| Phase | MSE | MAE |
|---|---|---|
| Training | 0.0989 | 0.1828 |
| Testing | 0.1016 | 0.1850 |

During training, the model achieved an MSE of 0.0989, while during testing, this value slightly increased to 0.1016. The small difference between training and testing performance suggests that the model is well-generalized and not overfitting. The pruned RTCNet model achieved an MAE of 0.1828 during training and 0.1850 during testing. These relatively low values indicate good prediction accuracy. Pruning allowed for a reduction in the number of parameters of the model while maintaining competitive performance. The application of pruning reduced the complexity of the model, which likely contributed to better efficiency during training and more efficient use of computational resources. As a result, even though the number of parameters was reduced, the model's performance was not significantly affected, demonstrating the effectiveness of this technique in improving performance while reducing memory footprint. Pruning allowed the RTCNet model to achieve good performance on the test data, with low MSE and MAE values, while improving the model's efficiency in terms of size and computational time. These results suggest that pruning is an effective strategy for optimizing complex models in regression tasks, while preserving their ability to generalize well to new data.

d) Predictions of the three properties by RTCNet

The performance of the RTCNet model was evaluated for predicting three essential soil properties, i.e., SOC, biomass, and fertility, by comparing the results obtained without noise and with Gaussian noise added to the training data. The following results show the MSE and MAE values for each property:

- Without noise:
  - SOC: MSE = 0.0281, MAE = 0.1334
  - Biomass: MSE = 2.26e-05, MAE = 0.0038
  - Fertility: MSE = 0.2763, MAE = 0.4140
- With Gaussian noise:
  - SOC: MSE = 0.0280, MAE = 0.1331
  - Biomass: MSE = 2.53e-05, MAE = 0.0040
  - Fertility: MSE = 0.2816, MAE = 0.4201

The results show that while adding noise slightly degraded the model's performance (increase in MSE and MAE), the predictions remained relatively stable. The MSE and MAE values for the noisy model are close to those obtained without noise, demonstrating the robustness of the RTCNet model against data perturbations.

## 6 Discussion

The results presented in the previous section demonstrate that the RTCNet model performs competitively when compared to several state-of-the-art models such as ANN + GAN, CNN-LSTM, and Transformer + CNN, under both clean and noisy conditions. The RTCNet model, though more computationally expensive and parameter-heavy, shows robust predictive accuracy across various performance metrics. In particular, it maintains a relatively low MSE and

MAE even when Gaussian noise is added to the data. This highlights its ability to generalize well and remain stable when faced with external disturbances, which is crucial for predicting soil properties in real-world scenarios where data quality can vary.

The ablation study reveals that each sub-model in RTCNet—CNN, RNN, and Transformer—contributes significantly to the overall performance. However, the removal of the CNN component surprisingly improves the performance of RTCNet slightly, demonstrating that the inclusion of the CNN may not always be necessary for achieving high accuracy. This could suggest that simpler architectures might be more efficient for some tasks, especially when computational resources are limited. The results also show the positive impact of regularization techniques such as dropout and architectural improvements, as seen in the RTCNet Optimized model. Although this optimized version requires more parameters and training time, it achieves better accuracy, particularly in noisy environments. The resilience to noise and improved performance suggest that deeper and more robust architectures, along with enhanced attention mechanisms, can be beneficial in complex regression tasks such as soil property prediction.

Finally, the pruning of the RTCNet model proved to be a promising technique for reducing model complexity while maintaining competitive performance. The pruned RTCNet achieved a balance between accuracy and efficiency, as the reduction in parameters did not result in a significant loss of predictive accuracy. This indicates that pruning can be an effective strategy to improve the efficiency of deep learning models without compromising their generalization capability.

## 7 Conclusion

In this study, RTCNet, a hybrid deep learning model, was proposed, which effectively predicts essential soil properties such as SOC and fertility. RTCNet incorporates advanced architectures, including RNNs, Transformers, and CNNs, to handle both spatial and temporal dependencies in soil data. The model's robust performance in noisy environments is one of its key strengths, making it particularly suitable for real-world agricultural applications where data often contains perturbations. The comparative study showed that while traditional models, such as ANN + GA and Transformer + CNN, performed well in noise-free conditions, RTCNet maintained superior accuracy even as noise was introduced into the data. Specifically, RTCNet exhibited a lower MSE and MAE, with a slight increase in error under noisy conditions. This highlights the model's ability to generalize well despite external disturbances, ensuring its practical utility for soil management and sustainable agriculture. Furthermore, the results from the ablation study confirmed that each component of RTCNet contributes significantly to its performance. However, removing CNN improves the RTCNet model and slightly places it above the Transformer + CNN model.

Looking forward, further enhancements in RTCNet's architecture—such as deeper networks, better attention mechanisms, and additional regularization techniques—could improve its predictive power and efficiency. The potential integration of RTCNet into soil management systems could support precision agriculture by enabling more accurate assessments of soil health, facilitating optimized fertilization and contributing to carbon sequestration efforts. Ultimately, RTCNet represents a step forward in leveraging deep learning for sustainable agricultural practices, making it a valuable tool in the face of global challenges such as climate change and food security.

## 8 Future Work

Although the RTCNet model has shown promising results, several avenues for future work can further improve its performance and applicability in soil property prediction:

- Hybrid models: Future studies could explore hybrid models that combine RTCNet with other machine learning techniques, such as ensemble learning or reinforcement learning, to further improve predictive accuracy.
- Interpretability: In soil property prediction tasks, model interpretability is crucial for understanding the underlying factors driving predictions. Future work could focus on enhancing the interpretability of the RTCNet model, allowing domain experts to better understand its decision-making process.
- Transfer learning: Exploring transfer learning techniques could enable the model to leverage pre-trained models from related domains, reducing the amount of labeled data required for training and enhancing performance on smaller datasets.


## Data Availability

The data used to support the research findings are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare no conflict of interest.

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