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The Role of CNN in Soil Detection

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Abstract. Soil is an important part of agricultural production and environmental health, and its physical and chemical properties directly affect crop growth and ecosystem stability. However, traditional soil testing methods such as gravimetric and time-domain reflectance (TDR) techniques, although accurate, have limitations such as being time-consuming, costly and complicated to maintain. To improve the quality of soil, the researchers proposed the method of combining Convolutional Neural Network (CNN) convolutional models with soil detection. In this paper, this will be collated and the measurements will be classified into three categories: soil water content detection based on CNN, soil contamination detection based on CNN, and soil microbial detection based on CNN models. Such classification can be effectively combined with hybrid models such as CNN, Gate Recurrent Unit (GRU) and Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), among others. The results show that the hybrid model has higher accuracy and stability in predicting soil water content, microbial activity and heavy metal contamination, which helps to improve soil health monitoring and management. Future research can further combine multiple models to improve the accuracy and application range of soil testing.

Keywords: Soil, hybrid models, Deep learning.

1. Introduction

Soil is a crucial component of the Earth's ecosystem, and its quality and properties have a significant impact on various aspects of the environment and human activities. Monitoring soil parameters such as moisture content, pollutant levels, and microbial communities is essential for understanding soil health, assessing environmental risks, and implementing effective management strategies. The researchers used Sentinel-2 images and focused on bands like the Red Edge and Near-Infrared (NIR) for effective moisture detection which showed that this approach could predict soil moisture with high accuracy, using indicators like the Normalized Difference Water Index (NDWI) and the Normalized Difference Vegetation Index (NDVI) [1]. Moreover, an approach leverages transfer learning, specifically employing the MobileNetV2 architecture alongside a customized Convolutional Neural Network (CNN) model which allows for efficient and accurate recognition of soil types, which is crucial for assessing areas potentially affected by pollutants [2]. In the experiment of CNN for soil microbial detection, an interesting article discusses the potential roles of soil microbiomes in plant growth and soil fertility. This research emphasizes the importance of beneficial soil microbes, particularly plant growth-promoting rhizobacteria (PGPRs), in enhancing nutrient uptake, synthesizing beneficial compounds for plants, and protecting them from diseases [3]. The study also highlights the need for more focused research on the functional aspects of soil microbiomes to better manage soil fertility and support high-yield agriculture.

In recent years, convolutional neural networks have emerged as a powerful tool in the field of image processing and pattern recognition [4]. These networks have shown great potential in extracting useful information from complex data, making them suitable for analyzing soil-related images and spectra.

This paper aims to explore the application of CNNs in the detection and quantification of soil moisture content, pollutants, and microbial communities. The introduction section will provide an overview of the significance of these soil parameters, the challenges associated with their measurement, and the potential benefits of using CNNs for this purpose.

The article will review the existing literature on soil monitoring techniques and discuss the limitations of traditional methods. Additionally, the essay will introduce the basic principles of CNNs and their application in other domains, highlighting their ability to handle large amounts of data and extract meaningful patterns.

The motivation behind this study is to develop a more efficient and accurate approach for soil analysis, which can contribute to improved soil management, environmental protection, and agricultural productivity. By leveraging the capabilities of CNNs, the paper hopes to overcome some of the challenges faced by current methods and provide valuable insights into the complex nature of soil systems.

2. Three different applications

This article divides the application of CNNs in soil detection into three categories based on different scenarios: soil moisture, soil microorganisms, and soil pollution.

2.1. Application of CNNs In Soil Moisture Detection

In the past, soil water content measurements have relied on in situ measurement methods (e.g., gravimetric, time-domain reflectance (TDR), resistive), remote sensing techniques, weather stations, and web-based monitoring. Despite the advantages of these methods, there are still some problems, such as the gravity method is accurate but time-consuming and destructive, and the TDR technique equipment is expensive and requires specialized maintenance [5]. To address these issues, the study introduced a CNN model. A hybrid model combining CNN, gated recurrent unit (GRU) and adaptive noise fully integrated empirical modal decomposition (CEEMDAN) was used to measure soil water content according to Ahmed et al. According to Figure 1, The specific steps are first CNN is used for feature extraction and each convolutional layer is optimized by the ReLU activation function and Adam optimizer. Then CNN is combined with the GRU layer using three layers of CNN for feature extraction and integrating the features through the GRU layer for predicting soil surface moisture content (SSM) to reduce training and testing errors. Finally, Adaptive Noise Fully Integrated Empirical CEEMDAN for adaptive decomposition of the input signal prior to modeling to ensure that information is not leaked into future testing and validation subsets [4].

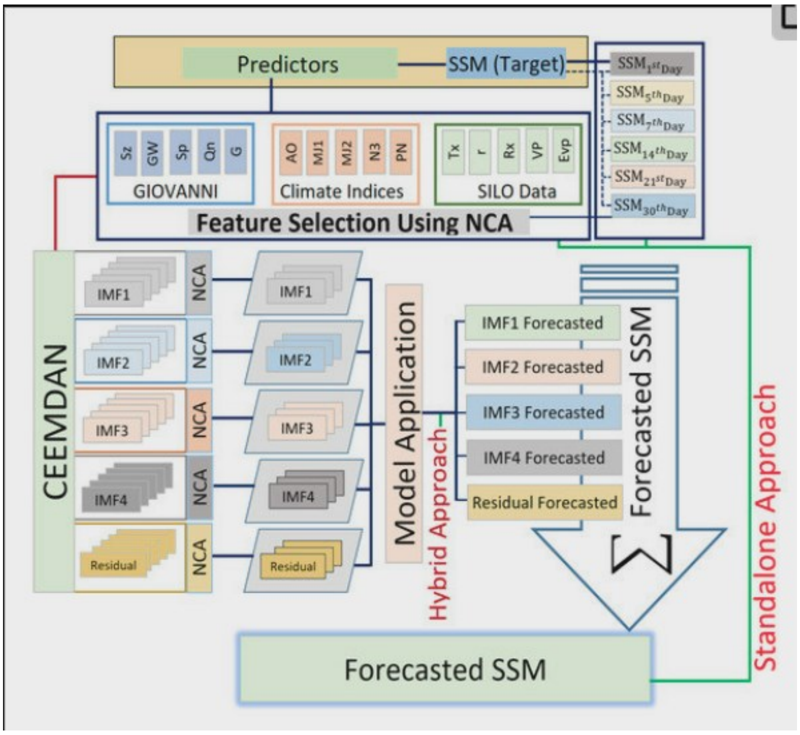

Figure 1. Experimental step [4]

A dataset from the Murray-Darling Basin, Australia, was selected for the study and combined with 21 climate indices for modeling. The daily SSM was predicted by a multi-step prediction model. According to Figure 2, The CEEMDAN-CNN-GRU model performed well in predicting soil moisture content, showing the smallest prediction errors at five different locations (Menindee, Deniliquin, Fairfield, Gabo Island) and over different time spans (1 day, 5 days, 7 days, 30 days). In contrast, the other models (e.g., CNN alone, GRU, and their combinations) generally show a larger error range, and the errors are especially significant in long-term predictions. The advantage of the hybrid model (CEEMDAN-CNN-GRU) is that it combines the spatial feature extraction capability of CNN, the time series processing capability of GRU, and the noise processing capability of CEEMDAN, which significantly improves the accuracy and stability of the prediction. Overall, the CEEMDAN-CNN-GRU model outperforms other models under various conditions, showing strong robustness and prediction performance.

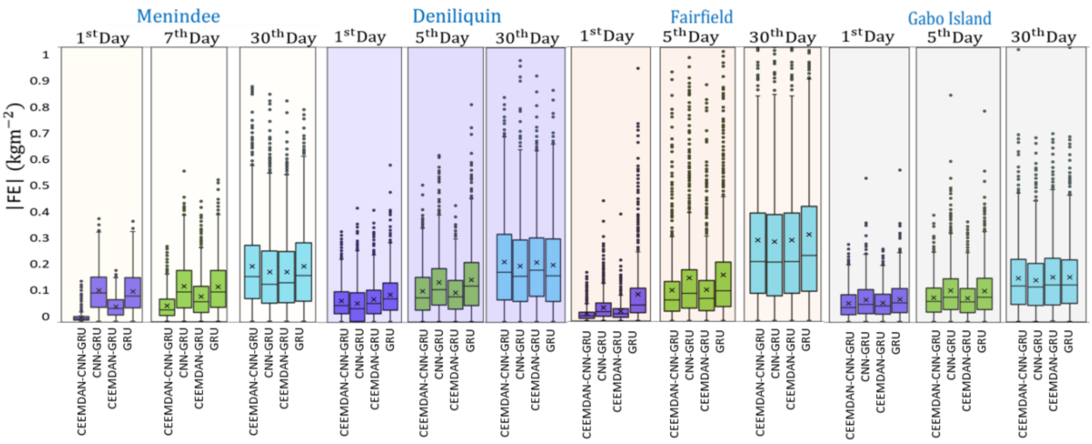

Figure 2. Result of experimental [4]

This experiment shows that the hybrid model outperforms the single model and the single model outperforms the traditional model. Not only this one experiment demonstrates the advantages of hybrid models, but also experiments such as the one by G. Kakamoukas et al. resulted in proposing a hybrid CNN and Long Short-Term Memory Network (LSTM) model for time series prediction. By combining the feature extraction capabilities of CNNs and the time series processing capabilities of LSTMs, the model achieved significant performance improvements on multiple time series datasets [6].

2.2. Application of CNNs in Soil Microbial Detection

Scientists have emerged in an endless stream of traditional methods to explore soil microorganisms, from the most primitive culture method, microscope observation method, to the later analysis of soil enzyme activity, these methods are slow to detect, and may not be able to detect all the existing microorganisms, especially those that are difficult to culture. And the accuracy is limited by existing technology. Moreover, the detection process is relatively transparent, which makes it difficult to explain the interactions and ecological functions between microorganisms. Moreover, the traditional method has higher cost and fixed object. Therefore, CNN-lstm model was introduced to detect soil microorganisms to optimize the traditional method. First, the geographical location data of soil samples (point data) is combined with peripheral information (such as climate, terrain and other environmental variables) to provide more comprehensive data input, which helps the model to more accurately capture the complex environmental characteristics of soil samples, thus improving the accuracy of prediction. Then, according to the research requirements and data characteristics, the window size (width and height) of the input data is determined, and a pixel is assigned to each soil sample location to facilitate processing in the image format and ensure that CNN can effectively extract local features. Then, environmental variables such as climate and terrain variables are included in the input data, and each variable corresponds to a channel, so that the model can simultaneously consider the impact of multiple environmental factors on soil samples, and improve the generalization ability of the model. Then convolutional filtering is used to process the input data, which helps the model capture the global and local patterns of the geographical environment and enhance the recognition ability of the model. Finally, a hybrid model including CNN and LSTM layers is constructed to improve the accuracy and efficiency of the prediction [7].

2.3. Application of CNN In Pollution Detection

One significant advantage of CNNs is their ability to automatically extract features from data, significantly reducing the need for manual intervention. This not only ensures more consistent and reliable results but also makes CNNs particularly useful when analyzing large-scale datasets [8,9]. Traditional ground monitoring methods often struggle to detect subtle changes in environmental data, but CNNs can capture these minute variations, leading to more comprehensive and accurate monitoring of soil pollution. This capability is especially crucial in soil microbial detection, where the presence and activity of microorganisms are closely linked to environmental conditions, requiring precise monitoring to understand their behavior and impact.

An illustrative example of CNN’s effectiveness is found in a study conducted by Muhammad Saqib Rashid and his research team [10]. In this study, 44 soil samples were collected from different regions of China to evaluate the soil’s physical and chemical properties, particularly its ability to adsorb cadmium (Cd) through the addition of biochar. Cadmium is a hazardous pollutant, and its accurate detection and monitoring are essential for environmental safety. To predict the concentration of cadmium in the soil samples, the researchers employed various machine learning models, including a 5-layer CNN, as shown in Figure 3. This CNN model utilized convolutional and pooling layers to extract and analyze complex patterns in the soil attribute data, leading to more accurate and reliable predictions than traditional methods could achieve. The CNN's ability to handle multivariate data and uncover hidden patterns in soil properties highlighted its potential to improve environmental monitoring.

The study also demonstrated that CNNs could be applied to understand the interaction between soil properties and environmental factors. By processing large and complex datasets, CNN models provided

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more detailed insights into the behavior of soil microorganisms, which is critical for developing effective soil remediation strategies. This automated approach not only enhances the precision of detection but also reduces the time and effort required, offering significant advantages over traditional monitoring techniques.

In conclusion, CNNs offer a robust and innovative solution for improving the accuracy and efficiency of soil detection. Their ability to automatically extract complex features, process large datasets, and provide precise predictions makes them invaluable tools in environmental monitoring. The study led by Muhammad Saqib Rashid exemplifies the practical applications of CNNs in soil science, showing how these models can enhance our understanding of soil properties and contribute to better environmental management. As CNN technology continues to advance, its integration into soil detection and analysis will play a crucial role in developing more effective soil remediation and management strategies, supporting sustainable agriculture and environmental protection efforts.

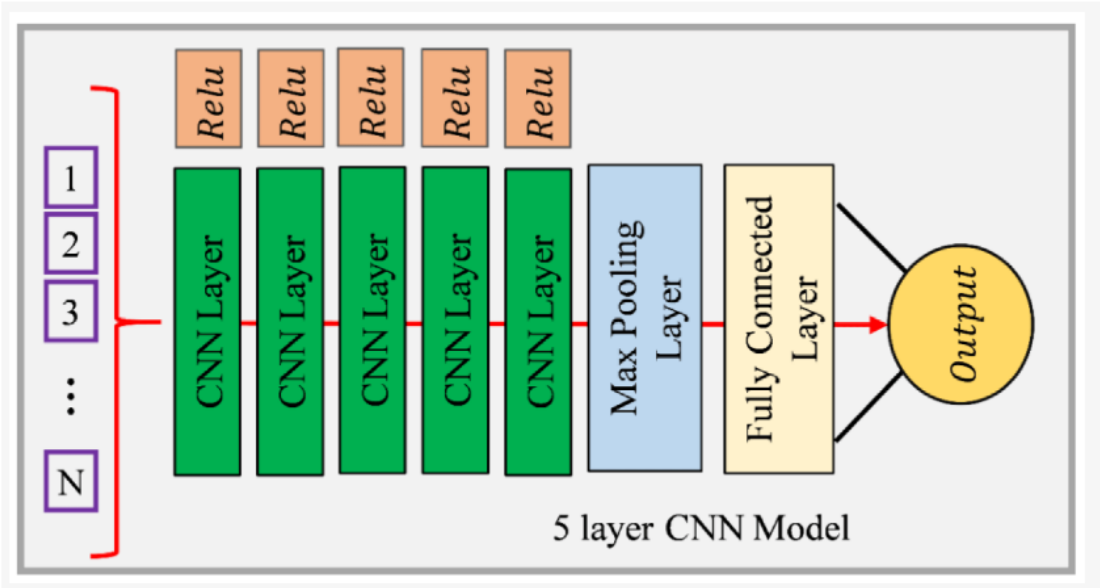

Figure 3. 5-layer CNN Model [10]

3. Conclusion

In this comprehensive review, the paper delves into the diverse applications of CNNS in soil detection, highlighting their remarkable benefits in three key areas: soil moisture content analysis, microbial detection, and pollution monitoring.

Firstly, CNNs have demonstrated exceptional accuracy in predicting soil moisture levels, especially when integrated with advanced models like GRU and CEEMDAN. This integration addresses the challenges posed by traditional soil moisture detection methods, which are often costly, labor-intensive, and time-consuming. The CNN-based approach not only optimizes the efficiency of moisture prediction but also makes the process more accessible by reducing the reliance on expensive equipment.

Secondly, in the domain of soil microbial detection, CNNs have significantly enhanced the detection process by automating feature extraction. This automation minimizes human intervention, which is particularly beneficial when handling large-scale datasets. By leveraging CNN's ability to process complex and high-dimensional data, microbial detection has become faster, more precise, and scalable, providing new opportunities for environmental and agricultural monitoring.

Finally, CNNs play a pivotal role in soil pollutant detection, specifically in improving the prediction accuracy of soil organic carbon and other harmful pollutants. By processing both spatial and temporal information, and combining with LSTM models, CNNs can better handle the complexities of environmental variables. This capability is crucial for addressing the intricate interactions between pollutants and soil properties over time, making CNNs a powerful tool in environmental monitoring and management.

In conclusion, the application of CNNs has not only enhanced the reliability, precision, and efficiency of soil detection methods but has also paved the way for the advancement of intelligent agriculture and environmental management technologies. Moving forward, future research should focus on exploring multi-model fusion techniques to further enhance the accuracy and applicability of CNNs in diverse soil detection scenarios, expanding their potential to tackle even more complex environmental challenges.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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