TerraTrack : Satellite Imagery & AI for Tracking Carbon Emissions

Abstract

Carbon emissions significantly impact global climate change, necessitating accurate and scalable monitoring systems. Recent advancements in remote sensing and deep learning provide innovative solutions for carbon emission detection and analysis using satellite imagery. In this study, we employed Convolutional Neural Networks (CNNs) for analyzing Sentinel satellite images to predict atmospheric carbon concentrations. This approach integrates advanced image preprocessing techniques with robust feature extraction to achieve high accuracy in carbon emission monitoring. Our framework is evaluated against metrics such as precision, recall, F1-score, and computational efficiency, offering a scalable solution to track carbon emissions in real-time. This research supports efforts to mitigate climate change by providing actionable insights into atmospheric carbon distribution. By leveraging data from the Sentinel satellite series, our proposed method stands out as a significant step towards real-time environmental monitoring. The study aims to fill the gaps left by traditional monitoring techniques by using advanced computational models to process and interpret large datasets. Additionally, we propose future enhancements that could extend the model's applicability to other pollutants and integrate additional environmental variables for holistic monitoring.

Keywords

Carbon emissions, satellite imagery, Convolutional Neural Networks, Sentinel data, deep learning, environmental monitoring, feature extraction.

I. Introduction

1.1 Importance of Carbon Monitoring

Climate change is a pressing global issue, driven in part by increasing atmospheric carbon concentrations. Monitoring carbon emissions is vital for assessing the environmental impact of industrial and agricultural activities, as well as for informing policy decisions. Accurate data on carbon emissions enable governments, organizations, and researchers to develop strategies for reducing emissions and mitigating their adverse effects on the environment. Traditional ground-based monitoring methods, while accurate, lack scalability and spatial resolution, creating a need for innovative solutions using satellite data.

1.2 Challenges in Carbon Detection

Current carbon monitoring methods face challenges such as limited data availability, high costs, and inefficiency in large-scale applications. Satellite-based monitoring provides extensive coverage, but the sheer volume and complexity of satellite data necessitate advanced computational methods. Variations in atmospheric conditions, cloud cover, and sensor noise further complicate accurate carbon detection from satellite imagery.

1.3 Deep Learning in Environmental Monitoring

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have revolutionized the field of image analysis. By leveraging the powerful feature extraction capabilities of CNNs, this study aims to predict atmospheric carbon concentrations accurately using Sentinel satellite imagery. CNNs are particularly well-suited for analyzing the spatial patterns and textures present in satellite images, making them an ideal choice for this application.

II. Related Work

Satellite-based carbon monitoring has gained significant attention in recent years. Studies utilizing the Sentinel satellite series have demonstrated the potential of remote sensing in environmental applications. The Sentinel-5P satellite, in particular, provides high-resolution data on atmospheric gases, making it a valuable resource for carbon monitoring. Other studies have explored the use of hybrid models that combine CNNs with other machine learning techniques.

III. Methods

3.1 Dataset Description

The dataset used in this study comprises high-resolution images captured by the Sentinel-5P satellite. These images provide detailed information on atmospheric gases, including CO_2 and CO concentrations. Preprocessing steps included georeferencing, normalization, and cloud masking to ensure data quality and consistency.

3.2 Model Architecture

The Convolutional Neural Network (CNN) model used in this study is designed to extract spatial features from satellite images effectively. Key components include Convolutional Layers, Pooling Layers, and Fully Connected Layers. Data augmentation techniques, such as rotation and flipping, were employed to enhance the model's generalization capabilities.

3.3 Experimental Setup

Experiments were conducted using Python and TensorFlow on a workstation equipped with an NVIDIA RTX 3090 GPU. The dataset was split into training (70%), validation (20%), and testing (10%) subsets. Performance metrics such as accuracy, precision, recall, and F1-score were used to evaluate the model's effectiveness.

IV. Results and Discussion

The CNN model demonstrated high accuracy in predicting atmospheric carbon concentrations. Key findings include training accuracy of 98.5%, validation accuracy of 96.8%, and testing accuracy of 95.2%. These results highlight the potential of CNNs in large-scale environmental monitoring.

V. Conclusion

This study presents a robust framework for monitoring atmospheric carbon emissions using Sentinel satellite imagery and Convolutional Neural Networks. By leveraging deep learning, the proposed approach achieves high accuracy and scalability, offering a valuable tool for climate change mitigation efforts.

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