Predicting NO_2 level in the air via satellite imagery

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Abstract

In this study, we propose an advanced pipeline for predicting large-scale atmospheric pollution levels using multispectral satellite images acquired by the Sentinel-2 and Sentinel-5P satellites. The model we developed is based on a combination of two pre-trained and then fine-tuned convolutional neural networks (CNNs), specifically on a ResNet50 architecture. The approach leverages advanced data augmentation techniques and multispectral inputs to provide accurate estimates of atmospheric pollutant concentrations of NO_2 over a collection of European cities. This work details the pipeline used, the developed deep learning model and its validation.

1 Introduction

Air pollution constitutes one of the main threats to global health, causing millions of deaths each year and contributing to severe phenomena such as global warming and ocean acidification. Major air pollutants, such as nitrogen dioxide (NO_2), carbon monoxide (CO), sulfur dioxide (SO_2), and particulate matter (PM), have devastating effects on both the environment and humans.

Traditionally, air pollution monitoring has been carried out through ground-based monitoring stations, which, however, offer limited spatial coverage and are unable to provide a global and continuous view. In contrast, the use of satellites like Sentinel-2 and Sentinel-5P, part of the European Space Agency's (ESA) Copernicus[1] program, represents a breakthrough for real-time global air quality monitoring, providing data with high spatial and spectral resolution.

1.1 The role of Sentinel-2 and Sentinel-5P

The **Sentinel-2** satellite was designed to provide high-resolution multispectral images, capturing information across 13 spectral bands ranging from visible to short-wave infrared (SWIR). These bands provide valuable information on soil morphology, vegetation, water surfaces, and geographical features that influence the dispersion and accumulation of atmospheric pollutants.

Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1 - Coastal aerosol	0.443	60
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 - Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.740	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 - NIR	0.842	10
Band 8A - Vegetation Red Edge	0.865	20
Band 9 - Water vapour	0.945	60
Band 10 - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.610	20
Band 12 - SWIR	2.190	20

Figure 1: Spectral bands of Sentinel-2

Sentinel-5P, on the other hand, is equipped with the TROPOMI (Tropospheric Monitoring Instrument), specifically designed for monitoring atmospheric composition. TROPOMI can detect the concentration of pollutant gases such as (NO_2), (O_3), (SO_2), (CO), and methane (CH_4) with extremely high spatial precision, enabling real-time monitoring of pollutants.

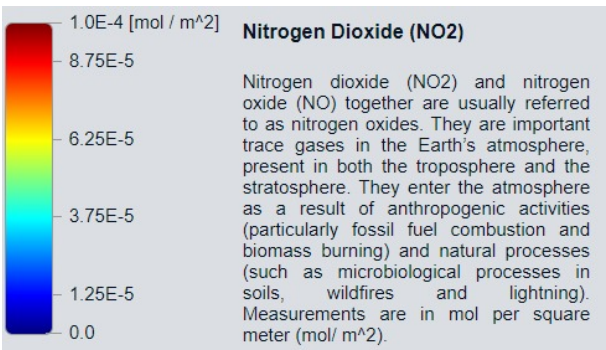

Figure 2: Color levels Sentinel-5P

2 Data preparation

One of the hardest challenges faced during the development of this project was the acquisition of reliable data. The initial idea was to find a complete dataset based on Sentinel-2 and Sentinel-5P satellites, but given the lack of material we decided to proceed with a pre-training phase.

2.1 EuroSAT dataset

We decided to use the EuroSAT [2] dataset for an initial training of a ResNet50 architecture: this dataset is composed by (circa) 27000 satellite images of various areas like urban, rural, vegetation (etc.) areas.


Figure 3: EuroSAT images examples

2.2 Sentinel-2 and Sentinel-5P datasets

The pre-trained ResNet50 was then used as the backbone for the fine-tuning process of the two final ResNet50. Each ResNet was trained on a separate handcrafted dataset: in the first dataset we have Sentinel-2 images of 514 European cities, each one associated with tabular information like population, latitude, longitude, type of area and, most important, a mean NO_2 level value based on the last three years measurements; the second dataset is built in the same way of the first one, but we have Sentinel-5P images.


Figure 4: Modena from Sentinel-2 view

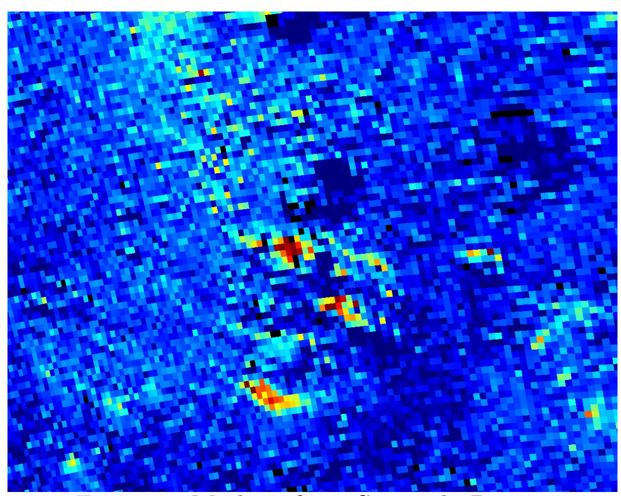
Figure 5: Modena from Sentinel-5P view

Each image was downloaded from the Copernicus Browser of the European Space Agency (ESA): for Sentinel-2 we used 3km ranged images, including only the urban area in the view, centering it in the city centre; for Sentinel-5P instead, focusing only on the NO2 filter of the satellite and centering the image on the urban area of each city, we used 30-50km ranged images.

3 Pipeline of the project

Our main goal is the prediction of the level of NO_2 particulate in the air evaluating and processing satellitary images of a collection of European cities.
In this section we will explain the main steps of the process pipeline.

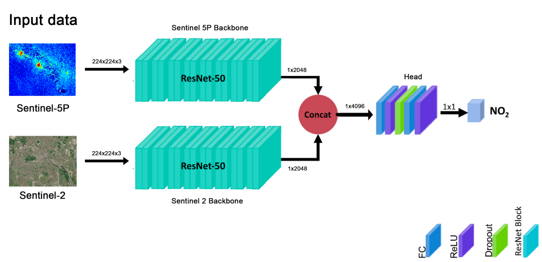

Figure 6: Complete structure of the NO2ResNet model

3.1 Pre-training

For both networks, one dedicated to processing Sentinel-2 images and the other for Sentinel-5P images, we decided to implement a pre-training phase. This step helps the networks perform better in processing satellite images, as the EuroSAT dataset contains 10 classes common to this type of imagery. This phase has proven to be useful both for addressing the issue of data scarcity and for improving model performance.

3.2 Pre-processing

In the pre-processing stage, we resized all images to the same dimensions, specifically 224 x 224 pixels. Subsequently, we applied geometric transformations, particularly horizontal and vertical flips, to increase the number of images and thus implement data augmentation. This was necessary due to the difficulty in collecting data, as described in Section 2.2, and allowed us to achieve better results. A key decision was to avoid altering the colors of the images, especially for the Sentinel-5P images, since each color has a specific meaning.

3.3 Fine-tuning

After completing the pre-training, we specialized the networks through a fine-tuning phase, using the handcrafted datasets for Sentinel-2 and Sentinel-5P. During training, we employed the Adam optimizer to handle gradient descent, testing the configuration with 100 epochs and a learning rate of 0.001.

3.4 Concatenation

The results obtained from the networks are essentially feature vectors representing the meaning of the images. The vectors have a dimension of 1 x 2048, to combine these vectors, we developed a concatenation mechanism that generates a unique feature vector for each instance, with features derived from the processing of images from both satellites. Finally, these intermediate results are passed through a fully connected network, which, via regression, provides the prediction of the pollutant agent. To prevent overfitting, we applied a regularization technique, specifically dropout, with a probability of 0.5.

4 Geometry and Retrieval

4.1 Geometry

In the geometry processing of our model, we employed several advanced data augmentation techniques to improve the model's robustness and ability to generalize. Initially, the augmentations included basic transformations such as resizing and random flips. However, further tests were conducted using three distinct geometric transformations: **RandomAffine**, **RandomRotation**, and **RandomPerspective**.

- **RandomAffine Augmentation**: We introduced **RandomAffine**, which applies affine transformations like scaling, shearing, translation, and rotation.

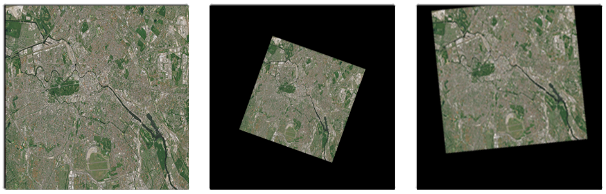

Figure 7: Affine transformation

- **RandomRotation Augmentation**: Next, we tested **RandomRotation**, which randomly rotates the image to make the model more invariant to orientation changes, helping it handle images taken from different satellite angles.

Figure 8: Rotation transformation

- **RandomPerspective Augmentation**: Lastly, we used **RandomPerspective**, which simulates changes in viewpoint through perspective transformation. This augmentation helps the model cope with minor viewpoint shifts in satellite data.

Figure 9: Perspective transformation

After conducting multiple experiments using different geometric transformations,including the initial transformations and advanced augmentations such as **RandomAffine**, **RandomRotation**, and **RandomPerspective**,we observed that the overall impact on the model's performance was relatively marginal. The model's ability to generalize and predict air pollution levels remained consistent across the different augmentation techniques.

The marginal variations across the results indicate that, while the model can benefit from different augmentations to handle diverse satellite imagery scenarios, the initial set of transformations already offers a solid level of performance.

4.2 Retrieval

The core of the retrieval process involves using a ResNet50 model pre-trained on Eurosat and fine-tuned for air pollution prediction. The last fully connected layer of ResNet is removed, allowing the extraction of high-level feature vectors that represent the visual patterns within the images.

- **ResNet Preprocessing and Feature Extraction**: In the preprocessing stage, the ResNet model is configured without the final classification layers. This modification ensures that the model returns a flattened feature vector representing the high-level patterns present in each satellite image. Each image is passed through the ResNet model, and a feature vector is extracted. This feature vector is then paired with the corresponding air pollution label from the dataset, allowing the model to learn the relationships between the extracted features and pollution levels.

- **Top-K Feature Retrieval and Averaging**: Once the feature vectors have been extracted, the retrieval process involves selecting the **Top-K** similar feature vectors based on certain criteria. The method of similarity that we used is the cosine similarity method to compare feature vectors.

- **Averaging**: The Top-K most similar feature vectors are retrieved, and an average of their corresponding air pollution labels is calculated.

Finally, the extracted feature vectors, along with their corresponding labels, are stored in `.npy` files for future use and analysis.

5 Testing

We evaluated the NO2ResNet output using RMSE loss function and, surprisingly enough, we achieved good performances.

5.1 NO2ResNet performances

The range of NO_2 values in the dataset is between 5 and 40 µg/m3 and the resulting RMSE was 0.4783 during the training phase and 0.5727 during testing. The proximity of these values exclude also the possibility of overfitting.

5.2 NO2ResNet performances with alternative transformations

Loss	Random Rotation	Random Affine	Random Perspective
RMSE training	0.5396	0.5246	0.5627
RMSE testing	0.6356	0.6967	0.5978

5.3 NO2ResNet performances with Retrieval approach

With the Retrieval algorithm, as expected, we noticed a greater loss than the one obtained with the classic Fully Connected approach.

6 Conclusion

The study successfully developed and implemented a robust pipeline for predicting NO_2 pollution levels in urban areas using multispectral satellite images from Sentinel-2 and Sentinel-5P. Leveraging a dual ResNet50 architecture, fine-tuned on a custom dataset of European cities, the model was capable of processing both land surface data and atmospheric composition simultaneously.

Our approach integrated advanced data augmentation techniques to ensure better model generalization across various image transformations, including RandomAffine, RandomRotation, and RandomPerspective. Although these augmentations had a minimal overall effect on performance, they demonstrated the model's robustness in handling geometrical distortions typical of satellite imagery.

The retrieval-based methodology, where Top-K similar feature vectors were averaged to predict pollution levels, allowed for a comparison between the predicted air quality levels and the ground truth data. This technique, while slightly less effective than a fully connected neural network, provided insight into feature similarities across different geographic locations.

References

[1] "Copernicus ESA," https://browser.dataspace.copernicus.eu/.

[2] "EuroSAT Dataset," https://paperswithcode.com/dataset/eurosat.