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Abstract

Enhancing Ozone Monitoring with Low-Cost Sensors and Deep Neural Network: A Novel Approach †

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Abstract: Ozone is a crucial component of the Earth's atmosphere, playing a critical role in protecting the planet from harmful ultraviolet radiation. However, its concentration can vary greatly across different regions with significant impacts on human health and environment equilibrium. The aim of this work was to calibrate a low-cost sensing platform, based on chemoresistive gas sensors, to monitor the environmental concentration of O_3. The ongoing on-field calibration is performed with a deep neural network using the concentration of O_3 collected by the local environmental protection agencies through certified tools as the gold standard.

Keywords: ozone; deep neural network; chemoresistive gas sensor; calibration

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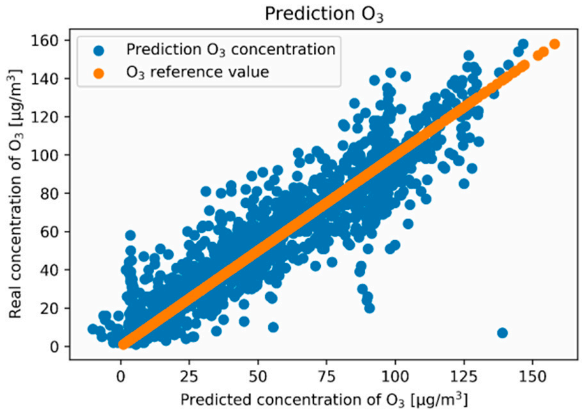
1. Introduction

Traditionally, ozone (O_3) monitoring has been conducted using expensive and complex instrumentation, which can be a limitation for its capillary mapping. However, recent advances in low-cost devices allow the development of affordable and accessible gas sensors that can support existing and established technologies [1,2]. The combination of low-cost sensors with machine learning (ML) techniques has opened new possibilities for improving the accuracy and reliability of O_3 measurements at high spatial and temporal resolution.

Several studies have shown that for environmental outdoor monitoring applications, preliminary low-cost sensor calibrations in the laboratory are not precise or sensitive. This depends on the impossibility of recreating the different conditions and gases that occur outdoors [1]. For this reason, we directly carried out on-field calibration through collaboration with local environmental protection agencies (EPA) that allowed us to compare our gas sensors with their certified tools.

2. Materials and Methods

The data were collected during an initial campaign in Trento, in conjunction with existing EPA platforms, employing 2 sensing platforms each arranged with 8 metal-oxide (MOX) gas sensors: the first in the city centre (Figure 1a) and the second near one of the city's busiest streets. The measurements are made up of the signals gathered by the 8 sensors on each platform, their heater resistances, temperature, humidity and pressure of the air. The per minute sampling data can be compared to certified data, which are provided as hourly averages of O_3 concentrations. The analysis was performed by processing data collected from January to September 2021, spanning three different seasons.



(**a**) (**b**)

Figure 1. (**a**) Sensing unit placed in the city centre of Trento, Park Santa Chiara; (**b**) model performance of the calibration method.

Firstly, we performed data cleaning in order to delete incomplete data and to identify those produced by non-functional sensors. The obtained values were linearly rescaled using the measurements collected during the two previous weeks to compensate for any time-dependent drift in the responses. The signals processed were aligned with the certified data collected by the EPA and divided into 3 disjoint sets: training, validation, and test. Calibration was performed by a deep neural network (DNN) trained with the first subset that took as inputs the values produced by the low-cost sensors and predicted the certified O_3 gas concentration. The hyper-parameters of the DNN were optimised with the use of the validation set. The last dataset was used to produce the predictions of the calibration model and to compare them with the measured concentration.

3. Discussion

The optimisation of the model was performed by minimising the mean square error (MSE), so the value of the R-square (R^2) estimator was a good statistical measure of the goodness of the model. The MSE obtained was 12 $\mu g/m^3$ with an R^2 of 0.873. The trend of the data is shown in Figure 1b; the predicted O_3 concentration values are on the x-axis and the measured values are on the y-axis. The model's predictions are least accurate when it comes to high concentrations. This is primarily because instances of high O_3 values are rare, making it difficult for the model to accurately replicate these values. Overall, our results suggest that the integration of low-cost sensors and ML algorithms can enhance the accuracy and accessibility of O_3 monitoring, making it possible to better understand and manage this critical atmospheric component.

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