Measuring Air Quality via Multimodal AI and Satellite Imagery

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Abstract

Climate change may be classified as the most important environmental problem that the Earth is currently facing, and affects all living species on Earth. One major driving force behind climate change is the pollution of the air which remains a key symptom of negative human influence on the environment. Air pollution is often invisible to the eye which can make its detection challenging unlike the destruction of the land or waterways. Given that air-quality monitoring stations are typically ground-based their abilities to detect pollutant distributions are often restricted to wide areas. Satellites however have the potential for studying the atmosphere at large; the European Space Agency (ESA) Copernicus project satellite, “Sentinel-5P” is a newly launched satellite capable of measuring a variety of pollutant information with publicly available data outputs. This paper seeks to create a multi-modal machine learning model for predicting air-quality metrics where monitoring stations do not exist. The inputs of this model will include a fusion of ground measurements and satellite data with the goal of highlighting pollutant distribution and motivating change in societal and industrial behaviors. A contemporary method for fusing satellite information with pollution measurements is studied, suggesting that simpler models can work as effectively as neural network models that are constructed with state-of-the-art architectures. A new dataset of continental European pollution monitoring station measurements is created with features including altitude, population density, environmental classification of local areas, and satellite data from the ESA Copernicus project. This dataset is used to train a multi-modal ML model, Air Quality Network (AQNet) capable of fusing these various types of data sources to output predictions of various pollutants. These predictions are then aggregated to create an “air-quality index” that could be used to compare air quality over different regions. Three pollutants, NO$_2$, O$_3$, and PM$_{10}$, are predicted successfully by AQNet and the network was found to be useful compared to a model only using satellite imagery. It was also found that the addition of supporting data improves predictions. When testing the developed AQNet on out-of-sample data of the UK and Ireland, we obtain satisfactory estimates though on average pollution metrics were roughly overestimated by around 20%.

Keywords: Air pollution, Air quality, Multi-modal AI, NO$_2$ estimation, O$_3$ estimation, PM$_{10}$ estimation

1. Introduction

Of all the issues currently facing humanity, the destruction and corruption of the Earth’s natural environment are the most pressing. The greenhouse effect, climate change, and rising sea levels have rightly entered the public consciousness – changes in the global climate driven by humanity are now well understood by the populace and we are beginning to see the perception of non-environmentally-humane organisations worsen. However, the problems of negative human activity are not limited to mass ecological damage, but also affect us as individuals too. Human influence on the quality of the air we share with all life on Earth continues to contribute to its degradation. With both a global and a local perspective, accurate and reliable systems of measurement must be implemented to influence societal and industrial behaviours. Remote sensors and the statistics that they produce inform us of changes in our environment. Given advancements in deep learning, the predictive capacity of remote sensing technologies is more capable than ever. Machine learning techniques have rapidly developed in power over the past decades and have the potential to unlock new methods of analysing environmental pollution that were previously untapped. In this paper, multi-modal machine learning techniques are applied in order to predict air-quality indices and illustrate airborne contamination in the places we live.
In response, we begin by discussing a background to pollution and remote sensing by satellite, followed by a detailed literature review on the state-of-the-art for machine learning in the remote sensing context. The proposed multi-modal ML model - AQNet - is then presented along with several comparison studies. AQNet is also tested in out-of-distribution data of the UK and Ireland. We conclude the paper with a brief summary and sharing of insightful remarks.

2. Background & Related Work

The negative impact of human beings upon the Earth manifests itself through the pollution that affects natural processes and environments wherever it acts, whether it may be: pollution of the seas and marine life; global warming; acid rain and smog; thermal pollution; groundwater poisoning; soil contamination; radioactive pollution; or even light and noise disrupting the natural world around us [1].

The contamination of the air can be the least visible when considering all the mediums we could pollute. Chlorofluorocarbons break down stratospheric ozone weakening our protection from solar radiation, while ozone itself within the troposphere is a key component of smog. Sulphur dioxide emissions from fossil fuel combustion poison the air we breathe and when mixed with water vapour form acids that rain down upon us. Nitrogen oxides also acidify rain and form photochemical smog – made worse by particulate matter aerosols that also may have the worse effect on the respiratory health of all airborne pollutants (See Table 1) [1].

| Pollutant | Common non-natural sources | Dangers |
|-----------|---------------------------|---------|
| Nitrogen Oxides \((NO, NO_2, \ldots, NO_3)\) | Combustion of coal and gasoline | Photochemical smog |
| Carbon Oxides \((CO, CO_2)\) | Incomplete combustion of fossil fuels | Toxicity by respiration |
| CFCs (Chlorofluorocarbons) | Aerosols | Degradation of the ozone layer |
| | Refrigerants | Reduced global coverage against solar radiation |
| | Industry | |
| Sulphur Dioxide \((SO_2)\) | Fossil fuel combustion | Respiratory system, health |
| Ozone \((O_3)\) | Reactions between NO\(_2\) and Volatile Organic Compounds | Health and ecological damage |
| Particulate matter \((PM_{2.5}, PM_{10} \text{ etc.})\) | Industrial processes | Myriad respiratory conditions |
| | Fuel combustion | |
| | Vehicle emissions | Smog |
| | | Catalysis of other atmospheric pollutants |
| Lead particulates | Gasoline combustion by automobiles | Toxicity |
| | Industrial processes | Brain damage |

Table 1: Common atmospheric pollutants and their dangers [1]

Additionally, the sources of air pollution are not always apparent at first glance. For example, in work collated by Harrison and Hester [2] studies at Heathrow Airport are showing that counter-intuitively “between 5% and 30% of the local NO\(_x\) contribution is related to aircraft, whereas the remaining 95% to 70% is from road traffic”.

Man-made environments themselves can impact air pollution in unforeseen ways which may result in poorer air quality relative to rural areas. The “urban heat island” effect leads to increased temperatures in cities, which as well as increasing air pressure and distribution can facilitate the rate at which secondary chemical reactions may take place, releasing more pollutants than otherwise [3].

Environmental pollution is a global issue that is only increasing in scale. Professor of Environmental Health Frank R. Spellman talked of pollution being defined as contamination – but concluding that in reality “Pollution is a judgment
transfer-learning. In their paper, Schneider et. al. should be an important step in reducing model scale. Nevertheless, studies including that of Johararestani et. al. include a requirement for sourcing suitable multitemporal samples upon which to run the model post-development. Evidence of a trend towards multimodal techniques increasing model predictivity, though key issues with this technique age data and LIDAR data fused together multimodally as input to neural networks [13]. Indeed, one may observe evidence of this in the body of the academic literature from 3 papers in 2014 to 73 in 2016 [9]. Sharma et. al. [10] developed an image-patched-based CNN approach to classifying RS imagery which they argued mitigated the lack of fine-grained structures often found within satellite images.

In 2019, LULC classification, object detection, scene recognition, segmentation, and change detection using RS imagery were the most common applications of ML in that order [11], with CNNs being the most commonly applied tool by a large margin. Heydari and Mountrakis compared NNet efficacy to that of classical SVMs and found that transfer-learning from pre-trained CNNs, despite often having only their RGB channel parameters non-randomly allocated, perform better than SVMs unless “rich feature maps” are extracted from datasets [12].

In the 2020s, according to Schneider et. al. [15] traditional NN methods remain in use with an emphasis on transfer-learning. In their paper, Schneider et. al. used random forests of decision-tree algorithms to create maps of $PM_{2.5}$ distributions around Great Britain, which could inform studies on exposure to $PM_{2.5}$. Matter. They conclude by highlighting the potential power of the Copernicus program in an ML/RS context. Otherwise, the field of ML in RS is ever-growing. From studies of drought [16] to water-quality [17], the robustness of machine learning methods and their ability to handle huge streams of input data make them important tools in supplying predictive insight to
Environmental remote sensing problems.

Since its launch, the Sentinel-5P (S5P) satellite has inspired the creation of much work. An early study by Guanter et. al. in 2015 used simulated S5P data to anticipate the potential for analysing chlorophyll fluorescence, given the precursor’s status as the “first imaging spectrometer to deliver a continuous spectral sampling of red and near-infrared spectral regions” \[18\]. Sentinel-5P’s lead instrument, TROPOMI has a resolution that provides an unprecedented level of detail to be studied. According to Efremenko and Kokhanovsky \[19\], this is high enough to be problematic and special care is required to retrieve the height of the pollution layers from raw sources, however, the study of tropospheric column densities is less taxing. NO\textsubscript{2} monitoring using TROPOMI (See Figure 1) is typical within the academic corpus; for example, S5P outputs were used by researchers to show the changes in pollution brought about by stay-at-home orders during the COVID-19 outbreak \[20\].

![Atmospheric Nitrogen Dioxide distribution](image)

Figure 1: Example of Sentinel-5P tropospheric nitrogen dioxide (NO\textsubscript{2}) measurements over Great Britain and Ireland

3. Methodology

3.1. Baseline Model \[21\]

In 2021, Scheibenreif released a paper with Mommert and Borth of the University of St. Gallen \[22\] which proposed a CNN approach to predicting air pollution distribution from Sentinel-2 and Sentinel-5P imagery alone, building upon earlier work and a novel dataset created by these same authors that year \[21\]. They later submitted an updated paper comparing their method to alternative means of prediction \[23\] and supplied updated code via GitHub\[1\].

\[1\]https://github.com/HSG-AIML/Global-NO2-Estimation
The summation of this work demonstrated that by using a pre-trained ResNet50 backbone from a LULC model as part of a simple CNN architecture, the fusion of S2 multispectral images with mapped distributions of tropospheric \( NO_2 \) (from S5P) and ground truth measurements from \( NO_2 \) monitoring stations, acceptance criteria for the regression of \( NO_2 \) pollution could be met. The authors published a dataset and associated paper [21] fusing Sentinel-2 and Sentinel-5P images with ground monitoring stations around Europe. This dataset (referred to as the “\( NO_2 \)-Dataset” henceforth) consists of 3,098 entries, one for each \( NO_2 \) monitoring station with each sample containing:

- Name and ID for each monitoring station.
- \( NO_2 \) concentration measured from said ground monitoring station that were extracted from the EEA’s open-source service, [24] and aggregated by mean from September 2018 to December 2020.
- A Sentinel-2 image consisting of 12 spectral bands. During the pre-processing of the images into the \( NO_2 \) dataset, images were corrected for atmospheric effects and cropped to 120×120 pixel size, equivalent to 1.2km squares, centred on each ground monitoring station. Since Sentinel-2 spectral resolution for each band ranges from 10m to 60m, upsampling on lower resolutions has been done to bring all band resolutions to 10m.
- A Sentinel-5P tropospheric \( NO_2 \) concentration image that has been extracted from the Copernicus Open API Hub [25], with resolution of 5×3.5km. Pre-processing has been applied to this data to remove clouds and negative weather conditions. Then, the S5P data has been mapped to a 10×10 km grid over Europe. Based on the position of each ground monitoring station, a geographically near sample of this mapped data has been saved, matching the time from an air-quality measurement being recorded on the ground to the nearest time that the Sentinel-5P satellite overflew that station.

The aforementioned data set - \( NO_2 \)-Dataset - was then used as the basis from which to train their machine learning models. Sentinel-2 and 5P data from the \( NO_2 \)-Dataset are used as input to a convolutional neural network structure (see Figure 2) as follows:

- Sentinel-2 images, size 120x120 covering 12 spectral bands are fed into a ResNet50 structure. They removed the classification layer of the ResNet50 architecture, which is leaving 2,048 neurons at the output layer.
- Sentinel-5P images, size 120x120 and are fed into a CNN structure with 2 convolutional and 1 fully connected layer of 128 neurons.
- These two input streams are concatenated, yielding a fused model with 2,176 features.
- These features are the fed into a final “Head” layer (of 2 fully connected layers and a ReLU activation layer) that outputs the \( NO_2 \) regression figure.

Their approach obtains a 0.55±0.03 R2-Score in predicting \( NO_2 \) concentration over the time frame of 2018-2020. Then, the authors argue that a ResNet50 model that is pre-trained on the BigEarthNet dataset in a land-use cover classification task led to an increased model performance of 0.57±0.04. That being so, the metrics they have supplied to evidence this claim show a relatively small improvement (0.02 R2-Score).

### 3.2. The Proposed Method - AQNet

In this paper, we propose a multimodal AI network that combines (1) multi-spectral satellite imagery from Sentinel-2, (2) low-resolution tropospheric \( NO_2 \) concentration data from Sentinel-5P satellite, and (3) tabular data that exploits some important information about the ground measurement centres, such as altitude, population density, station and area type. Our multimodal AI approach, named as AQNet, exploits these three types of input into an optimised machine learning architecture to create predicted outputs of three important air pollutants of \( NO_2 \), \( O_3 \) and \( PM_{10} \). By using the three predicted pollutant, AQNet calculated a generic air-quality metric, \( \alpha \) to better quantify the predicted pollutant findings. For the purposes of more focused applications of a single pollutant concentration estimation, AQNet gives users opportunity to predict only a single pollutant among \( NO_2 \), \( O_3 \) and \( PM_{10} \) (will be named as AQNet-single henceforth), and thus each of these outputs are named as optional output of the model. The general architecture of the AQNet model is presented in Figure 3.
Sentinel-2 backbone: AQNet exploits utilisation of low-power and accurate network architecture of MobileNetV3 as its backbone. MobileNetV3 \cite{26} is known to be fast in semantic segmentation like applications, and also is capable of adapting non-linearities like swish and applying squeeze/excitation in a quantisation friendly and efficient manner. In initial development stages of AQNet, we experienced more than 2 times running time gain via using MobileNetV3 with NO\textsubscript{2}-Dataset compared to widespread backbones such as ResNet50 (Scheibenreif et. al. \cite{23}) backbone, DenseNet121 \cite{27}, and ConvNeXt \cite{28}.

Sentinel-5P NO\textsubscript{2} backbone: Since S5P concentration data is a single band and same size imagery format input like S2 imagery, we follow the suggestions by Scheibenreif et. al. \cite{21} and utilised a 2-layer convolutional neural network (CNN) followed by maxpool and fully connected network (FCN) layers as for the S5P backbone. This provides us with a low-power and significantly smaller architecture as the S5P backbone.

Extracted features from both satellite backbones for the S2 and S5P information are then fused in a satellite head that consists of 2 layers of FCNs.

Tabular data backbone: One of the most important parts of the proposed AQNet is to use tabular data along with satellite data. AQNet exploits utilisation of low-power and accurate network architecture of MobileNetV3 as its backbone. MobileNetV3 \cite{26} is known to be fast in semantic segmentation like applications, and also is capable of adapting non-linearities like swish and applying squeeze/excitation in a quantisation friendly and efficient manner. In initial development stages of AQNet, we experienced more than 2 times running time gain via using MobileNetV3 with NO\textsubscript{2}-Dataset compared to widespread backbones such as ResNet50 (Scheibenreif et. al. \cite{23}) backbone, DenseNet121 \cite{27}, and ConvNeXt \cite{28}.
with satellite images and concentration measurements under a multimodal-AI architecture. The Tabular architecture we utilise is a basic 2-layer FCN with ReLu activation functions. Tabular backbone takes 8 text/numerical data as its input (altitude, population density and 6 boolean inputs for area and station type) and creates 32 features which then are fused with the satellite data in the regression head.

As can be seen from Figure 3, the regression head is designed to create three outputs of $NO_2$, $O_3$ and $PM_{10}$. Within AQNet architecture all three pollutants can be predicted at the same time, along with another option to predict pollutants one-by-one depending on some specific needs. In order to achieve a three-pollutant-output architecture, we develop a new dataset that is discussed in detail in the sequel.

### 3.3. 3-Pollutant Data Set

In this section, we present a new data set for the purpose of predicting air quality index. This new dataset has 1,316 entries (excluding British and Irish samples) from distinct ground stations for pollutants $NO_2$, $O_3$ and $PM_{10}$.

Acceptable levels of concentration of all various pollutants exist across the Europe [24] are set based on the WHO Air Quality Guidelines in particular. We set the highest acceptable limits for what should be deemed unhealthy concentrations of three pollutants depending on the guidelines mentioned above. Average pollution concentrations in the 3-Pollutant dataset relative to acceptance thresholds is presented in Table 3

| Pollutants | Average | Threshold |
|------------|---------|-----------|
| $NO_2$     | 17.39   | 10.00     |
| $O_3$      | 54.72   | 60.00     |
| $PM_{10}$  | 21.30   | 15.00     |

Table 3: Average vs. Threshold Concentrations in $\mu g/m^3$

In the context of air-quality, it should be noted that mean $NO_2$ and $PM_{10}$ figures within the dataset already exceed our thresholds for acceptable air-health. This may have an affect that models trained on the dataset may be found to overpredict poor air-quality. However, given thresholds were derived from WHO targets, it is unsurprising that average pollution scores could exceed them.

Figure 4 depicts distribution of stations depending on their countries. Examining Figure 4, the geographic distribution of monitoring stations in the 3-pollutant data set appears relatively diverse which should provide more resilience to models trained thereon ran upon new sources.

When we examine the distribution of each pollutant presented in Figure 5, we conclude that (1) the distribution of ozone is normally distributed and centred about 50$\mu g/m^3$, (2) the distribution of $NO_2$ and $PM_{10}$ are both positively skewed about central tendencies of 18$\mu g/m^3$ and 20$\mu g/m^3$, respectively, (3) the $PM_{10}$ distribution has high kurtosis, which may bias a predictive model if this distribution is not truly reflective of the global distribution of $PM_{10}$.

The two numeric features in the 3-pollutant dataset, which are “Altitude” and “PopDense” appear to have predictive power. After mean-aggregating the altitude feature to 50m bins (see Figure 6(a)) and population density to 250 person/m$^2$ bins (see Figure 6(b)), we observe (1) there appears to be clear trends relating altitude to pollutant concentration, (2) in general, as altitude increases the average concentration of ozone also increases sharply, (3) as altitude increases, average concentrations of $NO_2$ and $PM_{10}$ may be expected to decrease towards zero, (4) on the other hand, increases in population density are correlated with average $O_3$ concentrations decreasing, (5) there is evidence that as population density rises, so do concentrations of $NO_2$, and (6) average $PM_{10}$ concentration and population density do not appear to be correlated in the 3-Pollutant data set.
As of the last analysis of the 3-pollutant data set, in considering the predictive power of each binary feature:

\[
\text{Area Type} = \{\text{rural, urban, suburban}\}
\]

\[
\text{Station Type} = \{\text{traffic, background, industrial}\},
\]

many such features seem to influence pollutant concentration. In order to analyse this, we calculate the following
A statistic named “relative influence”

\[ RI = \frac{\phi_1 - \phi_0}{\phi_0 + \phi_1} \]  

where \( \phi_1 \) and \( \phi_0 \) denote average pollutant concentrations when a feature is true or false, respectively. In Figure 7, we compare this “influence” statistic across all 6 features and 3 pollutants. Examining Figure 7, we observe that stations in rural settings have decreased \( NO_2 \) and \( PM_{10} \), and increased \( O_3 \) concentrations. Furthermore, Urban and traffic features however have strong influence for increased levels of \( NO_2 \) and \( PM_{10} \) when “true” whilst being situated in suburban areas does not appear to have strong influence on average pollutant concentrations. In terms of each pollutant: (1) \( O_3 \) concentrations being high for rural is true, and low when urban and traffic features are false. (2) \( NO_2 \) concentrations are low when rural, industrial and background features are true, and high when urban and traffic features are true. (3) \( PM_{10} \) concentrations being low are most influenced by the rural feature being true, and highest when the urban feature is true.
3.4. Air Quality Index

To ascertain the efficacy of the developed model under 3-pollutant data set, we define an air-quality index. Our original motivation in carrying out this work for multiple pollutant predictions and the proposal of the 3-pollutant data set is to prototype a tool for predicting the air-quality of any region of interest. The revised dataset of 3 pollutants will be enough to illustrate the idea behind the creation of such an index, based upon the pollutant threshold values given in Table 3.

Under the consideration that each pollutant’s contribution to the air pollution is the same when higher that the threshold, we define our generic air-quality index of \( \alpha \) as

\[
\alpha = 1 - \frac{1}{N} \sum_{k=1}^{N} \frac{Th_k - p_k}{Th_k}
\]  

where

- \( \alpha \) denotes the calculated "air-quality".
- \( N \) is the number of pollutants to be aggregated.
- \( Th_k \) is the threshold for the \( k^{th} \) pollutant to be deemed at an unhealthy level.
- \( p_k \) is the predicted concentration of the \( k^{th} \) pollutant outputted by the model.

The air quality metric defined in (2) will create a metric ranging from 0 to \( \infty \). We quantify these values as given below:

\[
\text{Air Quality Quantification Steps} = \begin{cases} 
\alpha = 0 & \text{no pollution predicted,} \\
0 \leq \alpha < 1 & \text{presence of some pollution,} \\
\alpha > 1 & \text{unhealthy levels of pollution.}
\end{cases}
\]  

4. Experimental Analysis

We tested our developed approach, AQNet, under two experimental analyses: (1) model evaluation - compares the proposed approach to the baseline models from Scheibenreif et. al. [23]. (2) out-of-distribution test - a selection of 36 monitoring stations across Britain and Ireland are used to assess AQNet performance.

4.1. Model Evaluation

In the first set of experiments in this study, we test the performance of the proposed method - AQNet, under the newly developed and revised 3-pollutant data set in predicting \( NO_2 \) concentrations. In addition to (1) AQNet-single (1-pollutant output), and (2) AQNet (3-pollutant output), we also tested AQNet-single architecture without tabular data in order to see the effect of tabular data addition in the 3-pollutants data set. This architecture will be named as AQNet (No Tabular) henceforth.

In terms of the comparative analysis, we compared our three AQNet architectures with baseline models presented in [23], which are (1) Satellite model: exploiting the usage of S2 and S5P imagery for the purpose of predicting \( NO_2 \), (2) Local: a non-satellite ML approach to predict \( NO_2 \) via exploiting metadata provided by the EEA such as area type, population density, and (3) Open Street Map: also a non-satellite ML approach predicting \( NO_2 \) by using open-sourced data including infrastructure density, etc.

For the purpose of the first set of experiments, we presented performance comparison results in Table 4. Examining the results in Table 4, by developing a new ML approach of AQNet, we managed to improve \( NO_2 \) concentration estimation performance compared to the baseline models of Scheibenreif et. al. [23]. Reiterating key metrics, we see an improvement of approximately 0.1 with AQNet-single architecture to mean R2-score metrics - albeit over differing sample sizes and restricted training data. Furthermore, 3-pollutant-output AQNet architecture successfully predicted \( O_3 \) and \( PM_{10} \) in addition to \( NO_2 \) whilst having a similar R-2 score compared to satellite model[23]. It should also be noted that our simplest AQNet architecture without tabular data performed better than baseline models and showed the
success of the improved architecture in AQNet even without tabular data. For simplicity, we kept AQNet architectures only pre-trained with the ImageNet data set instead of BigEarth (LULC) data. For future versions of AQNet, this dataset can be exploited with a similar potential performance increase. Figure 8 depicts the percentage performance gain of the proposed AQNet architectures compared to the baseline models of Scheibenreif et. al.

| Model                  | Observation        | Pre-training     | R2-Score | MAE     | MSE     |
|------------------------|--------------------|------------------|----------|---------|---------|
| Local [23]             | 3K                 | –                | 0.65±0.02 | 5.18±0.16 | 48.01±3.42 |
| Open Street Map [23]   | 3K                 | –                | 0.34±0.03 | 7.22±0.14 | 88.29±4.07 |
| Satellite [23]         | 3.1K               | BigEarth (LULC)  | 0.57±0.04 | 5.50±0.14 | 58.47±3.32 |
| AQNet (No Tabular)     | 1.3K               | ImageNet         | 0.61±0.05 | 3.93±0.28 | 28.49±4.76 |
| AQNet                  | 1.3K               | ImageNet         | 0.55±0.07 | 4.37±0.34 | 33.59±5.19 |
| AQNet-Single           | 1.3K               | ImageNet         | 0.66±0.06 | 3.72±0.34 | 25.28±4.98 |

Table 4: NO2 concentration estimation results of AQNet in comparison to Scheibenreif et. al. [23] models.

Figure 8: Percentage performance increase/decrease of Proposed AQNet architectures compared to the Baseline models of Scheibenreif et. al. [23]. From left to right, bar-plots belong to the proposed model of AQNet (No Tabular), AQNet-Single and AQNet, respectively.

4.2. Out-of-distribution Analysis

In this second set of experiments in this paper, we utilised a selection of 36 monitoring stations across Great Britain and Ireland to assess the proposed model’s out-of-distribution performance. Using the multimodal-AI AQNet model trained on continental European monitoring stations, we now measure the performance of the British and Irish locations and analysed them in detail.

The collected predicted concentration results for each pollutant are then passed to the air quality metric calculation stage. Based on the equation in (2), Predicted-\(\alpha\) (the air-quality metric) was calculated for each British and Irish pollution monitoring station. these predicted values are then compared to the “true” \(\alpha\) score based on their average NO2, O3 and PM10 measurements. When plotting the true values of alpha versus their predicted values in Figure 9(a) and percentage error in Figure 9(b), we observe that although the model clearly has predictive capability, in general, \(\alpha\) is overestimated. Median \(\alpha\) being greater than zero suggests that the model is calibrated to detect too much pollution. An interquartile range of 18% describes the shape of the error distribution as tight, hence our predictions may be considered to be precise but not accurate enough.

In Figure 9(c) to (f), we depict absolute error scatter plot maps for NO2, O3, PM10 and air quality metric - \(\alpha\), respectively whilst (b) presents boxplots of % errors between the measured and predicted values of each pollutant. At first glance the model fitting was reasonably successful - fits on NO2 and O3 were close to parity, though PM10 levels appeared overestimated Figure 9(a). However, when examining individual percentage error for each pollutant, it is clear that predictions for all pollutants are overestimated by around 20% on average (Figure 9(b)); NO2 errors
Figure 9: (a) Regression plots of true and predicted values of each pollutant and air quality - $\alpha$. (b) Boxplots of % error between the measured and predicted values of each pollutant. (c)-(f) Absolute error scatter maps for $NO_2$, $O_3$, $PM_{10}$ and air quality metric - $\alpha$, respectively.

vary considerably which was not expected prior to experiments considering the quality of $NO_2$ fitting during model development. Median $O_3$ predictions are the closest of the three sets of predictions to parity. Even though $PM_{10}$ predictions look highly clustered with some over-estimation in (a) – % errors vary in a higher margin compared to other pollutants; this is perhaps a consequence of the small value range $PM_{10}$ measurements in the dataset that make a small error in value creating a high percentage. This can also be seen in $PM_{10}$ absolute error scatter map in (e).

From the scatter maps in Figure 9 (c)-(f), we observe that most stations within the out-of-distribution dataset are found in England (28). Stations are concentrated in the Liverpool-Manchester urban area and the London/South East urban area. Likewise, most of the stations in the OOD dataset are classed as being in urban, background environments. Also, altitude and population-density distributions are both positively skewed. Given the potential differences between continental European stations and British/Irish stations, these factors may have led the model to overestimate pollution. It should also be considered that perhaps environmental policies or simply the geographical qualities of GB and IE as island archipelagos lead to lower pollution averages compared to the continent. Finally, overprediction may just be a corollary of a dearth of training data.

4.3. Limitations and Potential Improvements

Upon completion of this work, many areas of improvement have become apparent. One key area that the modelling and dataset creation processes never considered was that of meteorology. Weather effects play a critical role in the transport of air pollutants [1], yet the model has no knowledge of these as input. Even if pollutant measurements are averaged over two years, an average rainfall, humidity, or temperature statistic as an input may have influenced model predictivity – in Johararestani et al. [14], it has been shown that wind speed and visibility were both highly important predictors of $PM_{2.5}$ concentration; data should have included many more features and reduced them during
development processes via feature selection techniques. Likewise, though the model could have had access to geographical information, it would not have extended further than the sovereign state where each pollutant monitoring station was located. Though we maintain that this should not have been included as a categorical feature within the model, it is plausible that data encoded as a lat-long pair, or some other location feature could have been a good predictor of pollution. Although LULC characteristics were likely encoded within the 12 bands of Sentinel-2 data, it is possible that given the improvements to predictivity yielded by the inclusion of categorical features as inputs to the model, an explicit statement of land-cover concentrations could have improved results. A more informed metric for air quality would be worth pursuing. Only three pollutants were modelled which might unlikely be sufficient in assessing air quality. Likewise, the weighting of each being equally “unhealthy” within the metric might unlikely reflect reality and will be revised in future work. One final potential limitation, not discussed until now is the question of whether a CNN is a correct tool for carrying out this task at all. As explained, CNNs have been the premier algorithm within machine vision over the last decade – but that does not guarantee that with the addition of additional non-image-based features a pure-neural network strategy would be ideal. Perhaps a mixed ML and Decision Tree approach may have led to a more successful prediction.

5. Conclusions

In this paper, we proposed a multimodal-AI architecture - AQNet - for air-quality measurement via a combination of satellite imagery information and some tabular information about the location of the interest. Particularly, we promoted a three-level input architecture taking (1) Sentinel-2 imagery, (2) Sentinel-5P NO\textsubscript{2} concentration image data, and (3) text/numerical data of altitude, population density, and some boolean variables defining the area and station type.

Our proposed AQNet architectures have flexibility to predict a single pollutant and/or three-pollutant of \(\text{NO}_2\), \(\text{O}_3\) and \(\text{PM}_{10}\). These predictions are then fed to a generic air-quality calculation stage which gives a notion of whether the region of interest is polluted or not. In order for this air-quality indexing to work, we created and developed a new data set - the 3-pollutant data set - consisting of around 1.3K measurements of the pollutants in the Europe region.

The considerable performance improvement of AQNet models under \(\text{NO}_2\) and 3-pollutant data sets and the OOD test has shown us various future research directions as we discussed in the limitations and potential improvement section above. Ongoing work includes developing much-advanced S5P and Tabular backbones substituting the CNNs and FCNs, along with the development of a much richer data set including S5P imagery of \(\text{O}_3\) and \(\text{PM}_{10}\) pollutants.

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