Machine Learning Tools to Assess the Impact of COVID-19 Civil Measures in Atmospheric Pollution

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ABSTRACT

In January, 2020, a new virus, named SARS-COV-2, was identified and announced to the public; in March the World Health Organization (WHO) declared a worldwide pandemic. To reduce the transmissibility of the new virus, the local authorities, worldwide, introduced a series of measures to flatten the curve. Many of the measures included some form of lockdown and movement restrictions. This unique coordinated worldwide reaction, created an opportunity for researching the effects of low traffic in air quality. In this work we research the relation between the COVID-19 measures and the Air Quality Index (AQI), using four pollutant gases (CO, O_3, NO_2, SO_2). Also, we used a variety of machine learning tools (DNN, DTR, K-NN, Lasso, LReg, MAdam, MGBR, RFR, Ridge) to estimate the accuracy of each method in the prediction of the concentration for each gas one week later. The results showed that after the strict COVID-19 restriction measures the concentration of each pollutant gas reduced rapidly and increased again after the relaxation of lockdown measures. Finally in cases like Australia, where the measures weren't as strict as other countries, no improvement observed.

CCS CONCEPTS

• **Information systems → Information retrieval**; • **Computing methodologies → Knowledge representation and reasoning**; **Machine learning approaches**.

KEYWORDS

environmental quality, neural networks, COVID-19, machine learning

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1 INTRODUCTION

On December 31, 2019, China reported to the World Health Organization (WHO) several cases of unusual pneumonia in Wuhan. On January 7, 2020, a new virus, named SARS-CoV-2, was identified and announced to the public. In the end of January, WHO declared worldwide public health emergency. In February outbreak begin in Italy and other countries around the globe and by the end of Match the epidemic turned into pandemic [18], which resulted on half of the World population to be under some form of lockdown [31].

In order to minimize the transmissibility of SARS-CoV-2 virus, the local authorities, worldwide, introduced a series of measures to flatten the curve. These measures includes international travel controls (e.g. flight prohibition between countries), restrictions in internal movements (e.g. restrictions in transportation between municipalities), public event cancellations (e.g. closure of theaters), restriction gatherings (e.g. limiting the amount of people over an area), closure of public transportation, closure of schools, stay home requirements (e.g. move outside the house only for work, emergency, etc) and closure of workplaces (e.g. closure of industries/commercial sector) [20]. All of the above measures had a profound effect in improving Air Quality Levels (AQL). Indicative examples involve countries such as China [23], India [7], Brazil [17] and Spain [30]. However, there are no clear indication on the significance of each major pollutant factor.

In the first time in humans' history that measures for restricting people's movements have been centrally applied by the governments. However, country lockdown actually decreases the environmental pollutants and thus these measures can act as a unique medium for evaluating the environmental impact of a clean technology in humans' society rather than implementing simulations. The current environmental models are based on simulations [5, 28]. However, these models haven't been sufficient tested in reality and it's not clear the magnitude of the benefits in the air quality. The worldwide lockdown creates a unique opportunity for researching the significance of traffic reduction in air quality changes.

In this work we will investigate how the fluctuations in specific pollutant factors diversify the air quality, for a total of 51 countries in the world, during COVID-19 period. In particular, we focus on the relation among carbon monoxide (CO), ozone (O_3), nitrogen dioxide (NO_2) and sulphur dioxide (SO_2) to the Air Quality Index (AQI). As AQI we define a numeric value indicating how polluted is the air. Typically AQI considers CO, O_3, NO_2, SO_2 and PM_{10} [19].

Also, a variety of machine learning methods will be trained using the COVID-19 measures and the concentrations of each one of the most dangerous pollutant gases (CO, O_3, NO_2, SO_2), which included in AQI. For each of the pollutant a different model will be created. In total four models per machine learning methods will be trained. As input we will use the weekly COVID-19 measures and the pollutant's mean concentration and it's standard deviation. The output will be the pollutant's mean concentration and it's standard deviation, one week ahead. The mean concentration and standard deviation for each pollutant will be calculated weekly for each country using Sentinel-5 TROPOMI satellite images, clipped in the boundary of each country.

2 RELATED WORK

The multiple lockdown cases, all around the globe, have provided the opportunity to research in depth the impact of traffic volume and industrial activities reduction/closure in atmospheric and air quality levels. In China, during and after the lockdown researches proposed a reductive trend in CO, O_3, NO_2, SO_2, PM_{10} and $PM_{2.5}$ concentrations [6, 9, 10]. In Hubei region during the lockdown period in January and February, 2020, the Aerosol Optical Depth (AOD) and the Angstrom Exponent (AE) decreased and increased respectively by 39.2% and 29.4% (in Wuhan only they decreased and increased by 31.0% and 45.3%). [25].

India is another country, in which has been observed reduction in pollutant factors [15, 24, 26]. The work of [1] compares the air pollution changes in India and China before and after the lockdown. Exactly they used real-time measured concentrations of $PM_{2.5}$ and NO_2 for 6 mega-cities in India and 6 mega-cities in China. For each concentration, an AQI is calculated ($AQI_{PM_{2.5}}$ and AQI_{NO_2}) before, during and after the lockdown. The lockdown resulted to a reduction of 45.25%($AQI_{PM_{2.5}}$) and 64.65%(AQI_{NO_2}) in China and 37.42%($AQI_{PM_{2.5}}$) and 65.80%(AQI_{NO_2}) in India after the lockdown.

In Dhaka city (Bangladesh) the same phenomenon has been monitored using Internet of Things (Iot) [21]. In this case the pollutant factors measured were CO and NO_2 and the employed sensors were RADAR, Satellite, ionosonde and IoT sensors. In Baghdad (Iraq) [8] the daily concentrations of NO_2, O_3, $PM_{2.5}$ and PM_{10} used before and during the lockdown, in addition to the AQI for the same time period. In Madrid and Barcelona (Spain) [2] the concentration of NO_2 reduced 62% and 50%, respectively, after a 75% in traffic volume.

3 PROPOSED METHODOLOGY

The estimation of pollutant factors entails to a traditional regression problem [12]. Let us denote as $\mathbf{x} = [x_1, ..., x_n]$, a set of predictive factors, and $\mathbf{y} = [y_1, y_2]$ as the investigated pollutant factor and its standard deviation. We will try to estimate a predictive function $f(\mathbf{x}) \longrightarrow \hat{\mathbf{y}}$, where $\hat{\mathbf{y}} \simeq \mathbf{y}$ [13]. In our case we use for calculations $n = 10$ numeric values, analytically described in Section 4.1 and estimates the density of a pollutant factor one week ahead. This is achieved using a variety of models, including traditional approaches, as well as deep learning methods.

The dataset is a combination of the weekly COVID-19 measures and the concentrations of the most harmful pollutant gases (CO, O_3, NO_2 and SO_2) in a total of 51 countries worldwide. The following COVID-19 induced mitigation strategies have been considered as predictive factors for the pollution levels estimation:

- **Restrictions of Internal Movements**: includes all the measure which restricts the transportation between municipalities.
- **International Travel Controls**: includes all the measures which restricts/prohibits the transportation between countries.
- **Cancellation of Public Events**): includes the cancellation of all locally (e.g. football matches, concerts) or worldwide (e.g. Olympic Games in Japan, Euro-vision) public events.
- **Restriction Gatherings**: include the measures which restricts the number of people, which can be together in the same place.
- **Close Public Transportation**: includes the measures taken about the closure of public transportation (e.g. metro).
- **School Closures**: includes the measures taken about the education (e.g. school closure, distance learning, etc).
- **Stay Home Requirements**: includes the measures which restricts the people to move outside of their home without a specified reason (e.g. work, super-market supply, etc).
- **Workplace Closures**: includes the closure of the industrial activity and the commercial sector.

The COVID-19 dataset has been downloaded from Our World in Data (https://ourworldindata.org/policy-responses-covid) [20], which been updated daily. The concentrations of the four pollutants have been downloaded from the Sentinel-5/TROPOMI dataset of Google Earth Engine [3], in a weekly scale. These datasets will be used, in addition to the regression problem, for the calculation of the AQI and the qualitative estimation of the total impact of the above measures have in air pollution problem.

3.1 Machine Learning Tools for Extracting Environmental Impact

In this research the following machine learning approaches have been used:

- **Deep Neural Network (DNN)**: A DNN method is consisted of a deep and large net, which can surpass the eight hidden layers, with a few thousand hidden units per layer and full connectivity between the adjusted layers. The final calculation of the weights uses the standard discriminate, back-propagation algorithm, while the starting weights are initialized, randomly, by using an unsupervised learning algorithm without any knowledge of the labels[4].

  For the purpose of this research we used for input a set of predictive values $\mathbf{x} = [x_1, ..., x_n]$, and as output $\mathbf{y} = [y_1, y_2]$. The architecture, also, consists of three hidden layers (L_1, L_2, L_3), with sizes 20, 10 and 20 accordingly. As activation function between the hidden layers, the SELU (Scaled Exponential Linear Units) has been chosen, and for the output the SIGMOID.

- **Decision Tree Regressor (DTR)**: A DTR method is defined by a set input features and the output is a decision for the corresponding input. In the tree structure, each internal node tests an attribute and each of the nodes is assigned to a regressor[22]. The main parameter a DTR need for running appropriately is the maximum depth of the tree. In our case we used a $maximumDepth = 5$.
- **K-Nearest Neighbor (K-NN)**: K-NN is a supervised machine learning method. In the method are calculated the distances (usually Euclidean) between a x_i feature and all features of the training set. Then the k-nearest neighbors are selected and the x_i feature is classified with the most frequent class among the k-nearest neighbors[14].
- **Lasso**: This method solves the linear regression algorithm depended in the calculation of a coefficient bounds, using a tuning parameter named λ. Lasso algorithm can be explained further by the LARS algorithm[29].
- **Linear Regression (LReg)** can be expressed as the statistical method applied to a dataset to quantify and define the relation between the considered features. LReg can be used for forecasting. We have, also, consider other types of linear models, fitted by minimizing a regularized empirical loss with **Stochastic Gradient Descent (Multi O/P GBR - MGBR)**, or by fitting a regressor on the original dataset and then fits additional copies of the regressor on the same dataset but where the weights of instances are adjusted according to the error of the current prediction. As such, subsequent regressors focus more on difficult cases (**Multi O/P AdaB - MAdaB**)[16]. In both training methods (MGBR and MAdab) we used $estimators = 5$.
- **Random Forest Regression(RFR)** RFR is an alternative of the DTR (in case of regression can be called regression tree - RTR - as well) methodology. In this case the concept of the DTR(RTR) can be extended using the power of contemporary computers to generate hundreds of DTRs(RTRs), simultaneously, known as random forests. The final prediction can be estimated by the smallest MSE calculated from the average of the various DTRs(RTRs)[27, 32]. RFR takes as parameters the maximum depth and a random state. We used $maximumDepth = 5$ and $randomState = 2$.
- **Ridge** regression is an important statistical method for modeling the connection between a depended scalar variable with one or more explanatory variables. It can take a large amount of training values as an input. The output is a curve (i.e. a parameter vector), which best fits the input values and can be used for predictions of classifications later[11].

4 EXPERIMENTS

4.1 Dataset description

The dataset is composed by 51 countries all over the world. For each country has been calculated the measures per week started from the 1st of January, 2020, as the first day of the first week. This methodology split the year into 52 weeks. For each week has been calculated the mean values of the COVID-19 measures described in Section 3. The raw COVID-19 measures dataset can take integer values between 0 (no measures) to 4 (strict restriction). However after the week calculation of the measure it can be any real number between 0 and 4.

The pollutant concentrations of the most harmful gases (CO, O_3, NO_2 and SO_2) has been downloaded from Sentinel-5P/TROPOMI satellite from Google Earth Engine API[3]. To be more specific only the density band which represent the concentration of pollutant per pixel in mol/m^2 unit has been downloaded. As clipped geometry has been chosen each country's boundary with a pixel size of $5km \times 5km$. The final pixel density has been calculated as the mean density per week. Furthermore for the linear regression to run the image needed to be transformed as a scalar value. The transformation achieved by calculated the mean and standard deviation per country for each of the four pollutants.

Finally, the two datasets combined and for each country the train/test input compromised from the 8 COVID-19 measures and one pollutant, out of four in total, (mean and standard deviation for the current week), while the train/test output compromised from the mean and standard deviation for the next week. In the end, experiments were based on a dataset of size 10 feature values $\times$ 52 weeks $\times$ 51 $countries$.

Also for each week the AQI has been calculated using the following equation[33]:

$$AQI = max(\frac{CO}{10,000}, \frac{O_3}{100}, \frac{SO_2}{125}, \frac{NO_2}{90}) * 50 \quad (1)$$

4.2 Experimental results

Table 1: Maximum Error and Mean Absolute Error (MAE) for each pollutant per method.

Technique	Data	CO	NO2	O3	SO2
DNN	Max Error	0.159333	0.000179	0.139547	0.002745
	MAE	0.005536	0.000058	0.014318	0.000171
DTR	Max Error	0.135728	0.000084	0.148739	0.002252
	MAE	0.002494	0.000005	0.006046	0.000082
K-NN	Max Error	0.157760	0.000066	0.137569	0.002570
	MAE	0.003363	0.000007	0.008709	0.000102
Lasso	Max Error	0.157038	0.000065	0.127353	0.002608
	MAE	0.005535	0.000014	0.014445	0.000154
LReg	Max Error	0.042808	0.000071	0.138866	0.002312
	MAE	0.002021	0.000005	0.006814	0.000092
LSTM	Max Error	0.173380	0.012420	0.133648	0.011848
	MAE	0.014625	0.006301	0.015396	0.004896
MAdaB	Max Error	0.082521	0.000069	0.131678	0.002300
	MAE	0.003542	0.000006	0.009641	0.000096
MGBR	Max Error	0.128519	0.000065	0.135054	0.002466
	MAE	0.003841	0.000010	0.010333	0.000119
RFR	Max Error	0.077991	0.000074	0.147247	0.002210
	MAE	0.002138	0.000005	0.005952	0.000082
Ridge	Max Error	0.064698	0.000060	0.138080	0.002596
	MAE	0.002643	0.000014	0.007059	0.000154

Table 1 demonstrates the Max Error and the Mean Absolute Error for each pollutant gas for each technique. The best result for each pollutant obtained from: (a) Ridge, for the CO gas, (b) Ridge in the

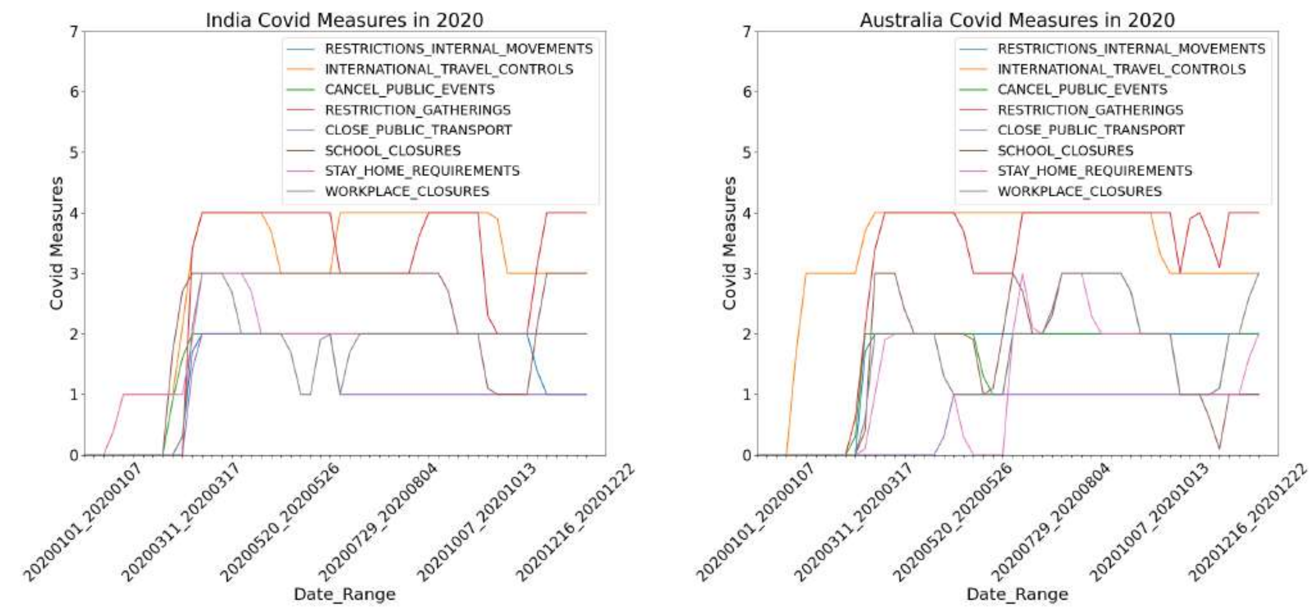


Figure 1: The 8 measure parameters used as training/testing inputs for India. 0 value indicates no measure and 4 value indicates the strictest measure. (Left: India, Right: Australia)

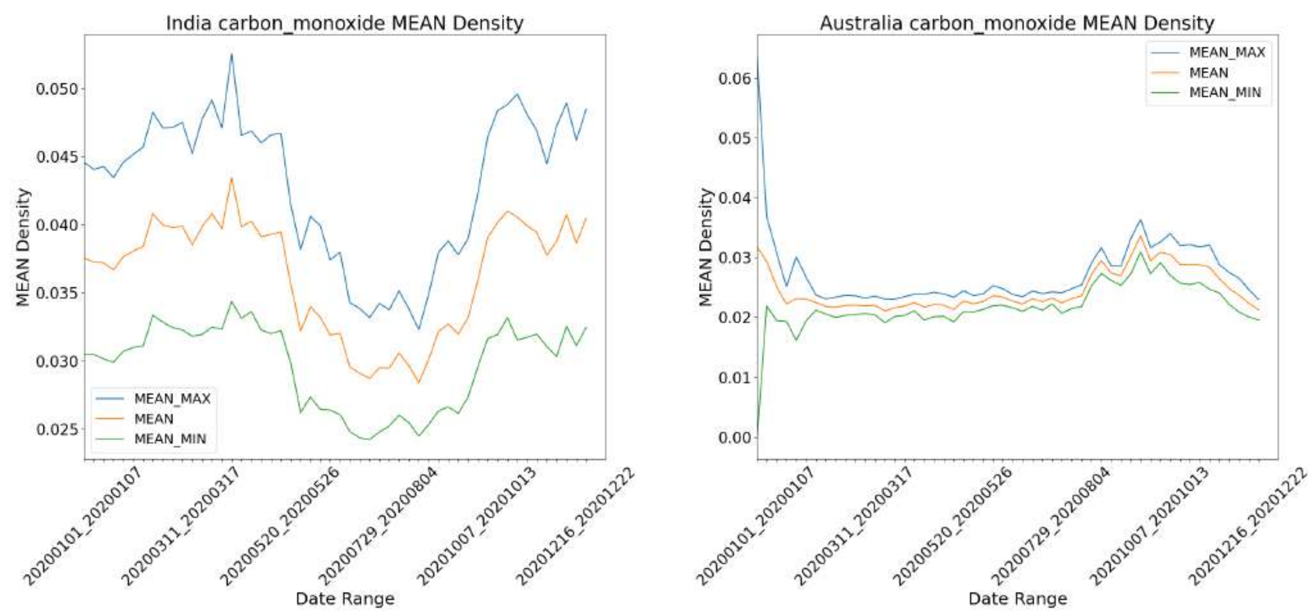


Figure 2: The mean concentration values of carbon monoxide ± the standard deviation. (Left: India, Right: Australia)

Max Error and from LReg in MAE, for the O_3 gas, (c) Ridge, for the NO_2 gas and (d) RFR, for the SO_2 gas.

Figure 6 illustrates the average root mean square error (ARMSE) for the test set of CO and O_3 gases. The best performance is observed for Lreg and RFR, respectively. A similar analysis is presented in

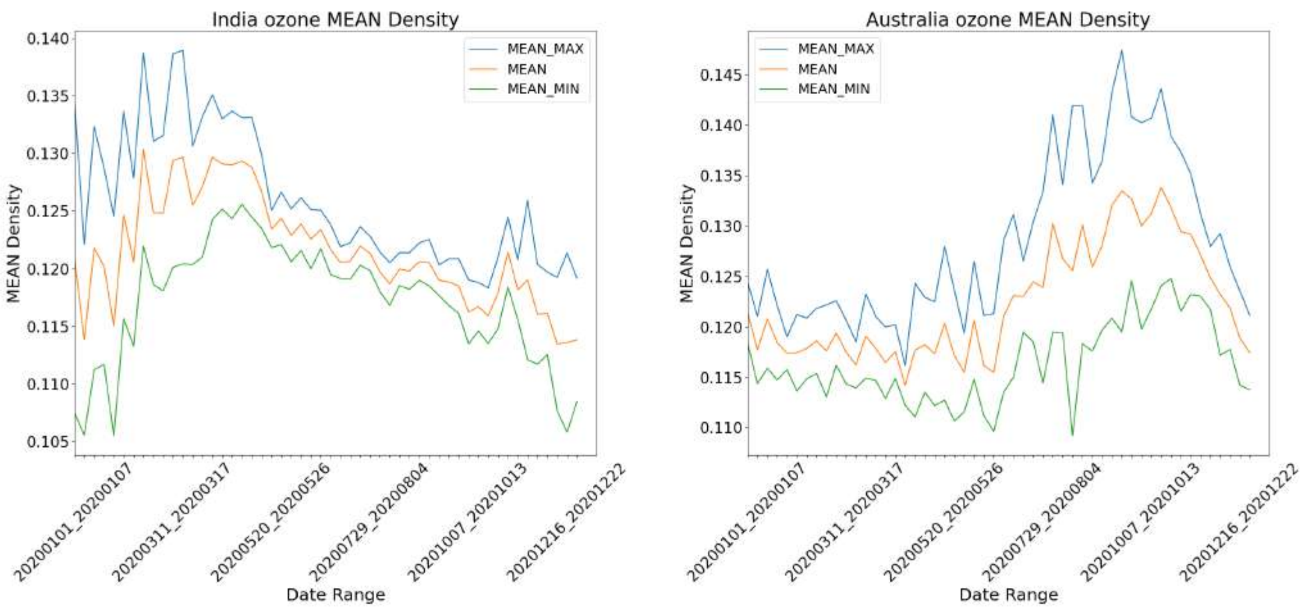


Figure 3: The mean concentration values of ozone ± the standard deviation. (Left: India, Right: Australia)

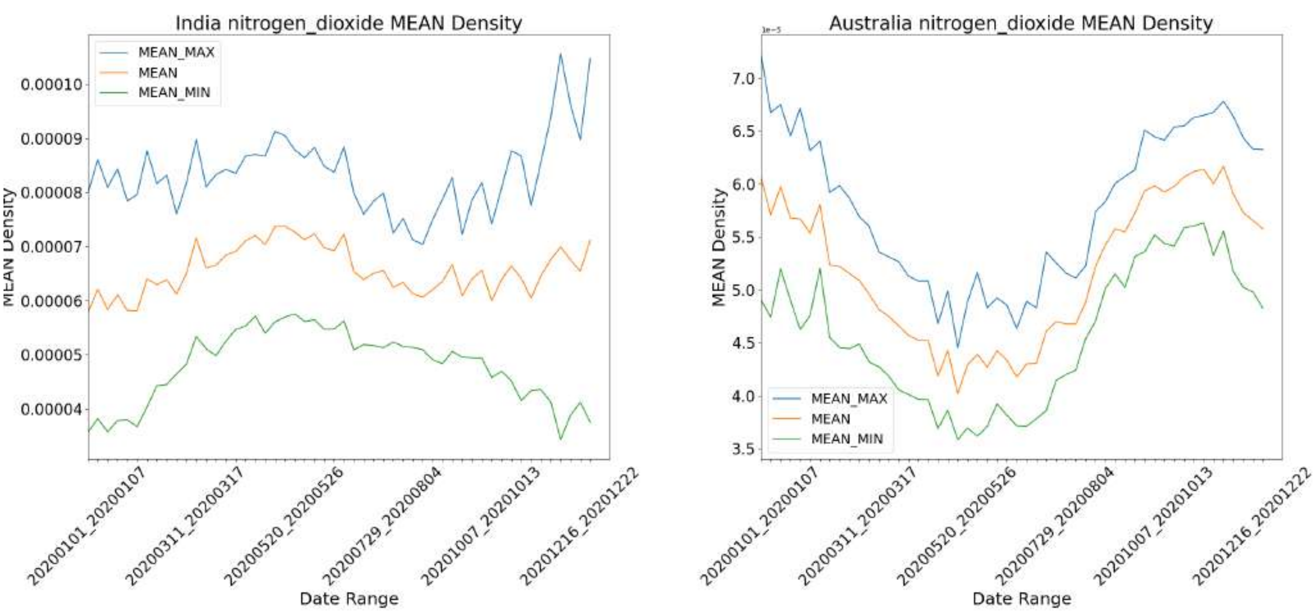


Figure 4: The mean concentration values of nitrogen dioxide ± the standard deviation. (Left: India, Right: Australia)

Figure 7 for the NO_2 and SO_2. In this scenario RFR performed better than the alternatives.

Figure 8 presents the AQI indexes for India (Left) and Australia (Right) as calculated from equation 1. O_3 gas impacts more than the other gases in the calculation of AQI. In the case of India where the total of measures (Fig. 1) were stricter than the Australia case, we observe that the AQI consistently decreased. In the Australia case, where the internal movement, and especially the closure of public

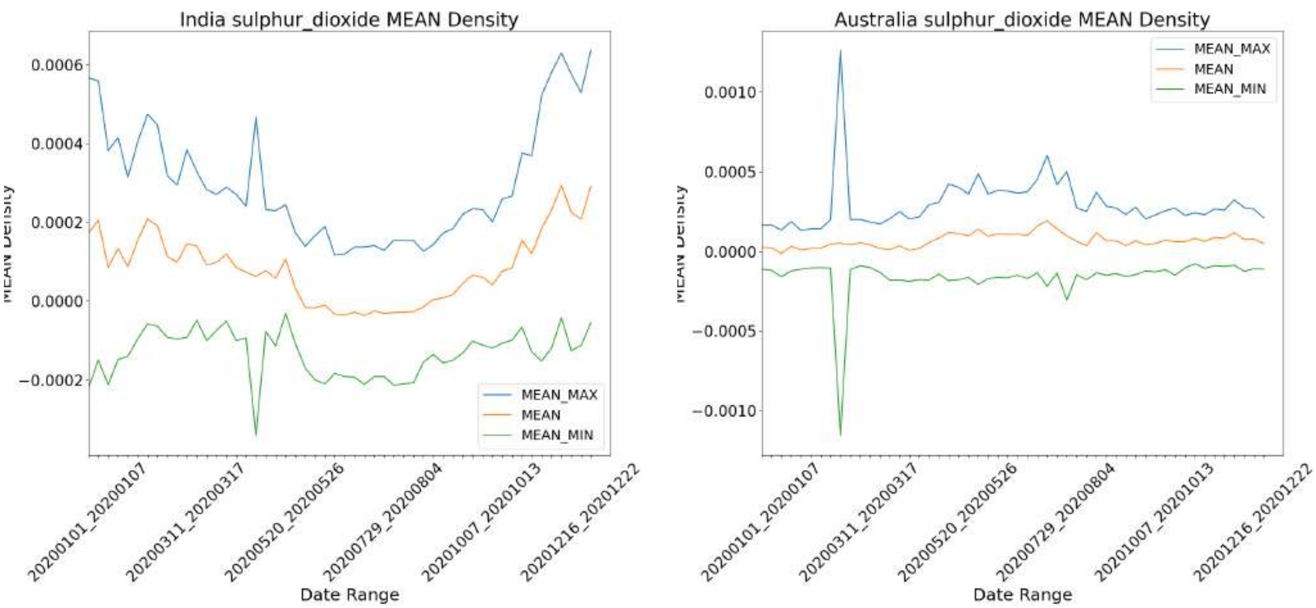


Figure 5: The mean concentration values of sulphur dioxide ± the standard deviation. (Left: India, Right: Australia)

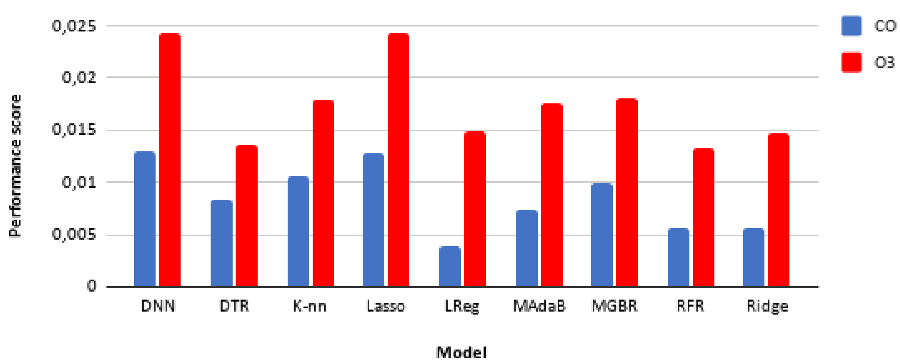


Figure 6: Average Root Mean Square Error (Performance Score) for CO and O_3 gases. The lowest value the better.

transportation was low (level ≤ 1) compared to India's (level ≥ 1) and the stay home requirement was at level ≤ 2, for the most part in the year (Australia), and level ≥ 2 in India, we observe consistently increment at the AQI.

5 CONCLUSIONS

In this work we indicated that a relation between the COVID-19 measures and the changes in air quality exists. To prove this relation we calculated the AQI for each of the 51 countries using the equation 1. The qualitative comparison between the figures 1 and 8 prove that in countries like India where the lockdown restrictions were in high level the AQI decreased consistently (approximately a 14.7% decrements from January till July, 2020). On the other hand, in Australia with low level restriction observed a linear increment of approximately 11.8% in AQI after May, 2020. Furthermore, from Table 1 and Equation 1 we conclude that the ozone affects the AQI more than the others.

Figure 2 indicates that CO in India decreased 25% from March to August (the lockdown measures started in February, Fig. 1) and increased 25% from August to October. For the same periods the O_3, NO_2 and SO_2 decreased(↓) or increased(↑) by ↓ 5.5% and ↓ 20.0%, ↓ 14.3% and ↑ 10.0%, and ↓ 90.9% and ↑ 900.0%, respectively. The above statistics proves that in India during the strict lockdown period the concentrations of the pollutants decreased, but after the relaxation of the measures the concentrations of CO, NO_2 and SO_2 which depends on traffic volume and industrial activity increased.

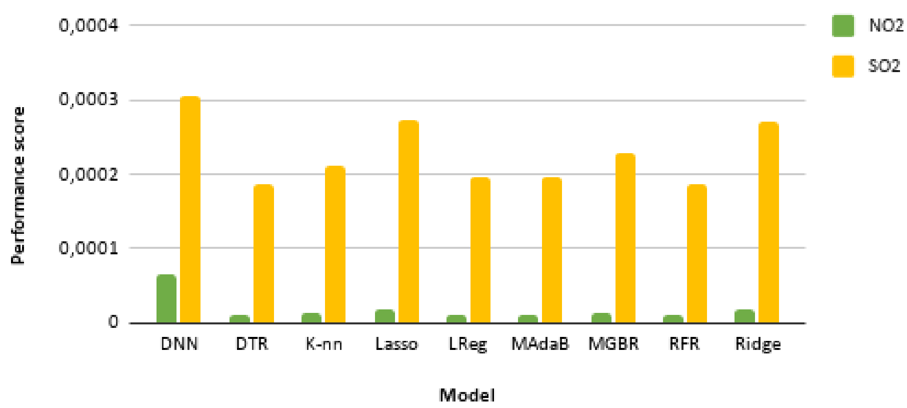
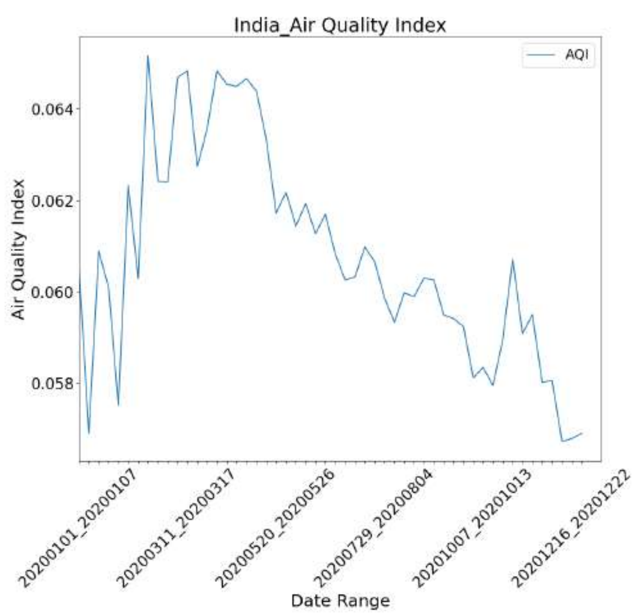


Figure 7: Average Root Mean Square Error (Performance Score) for NO_2 and SO_2 gases. The lowest value the better.



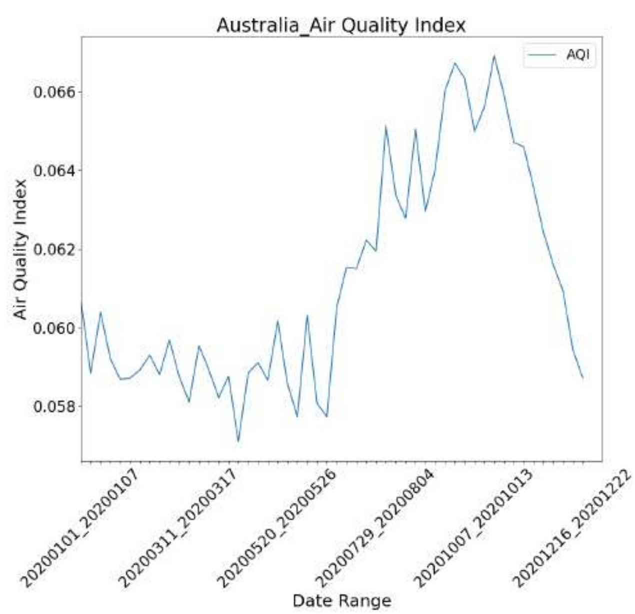


Figure 8: The Air Quality Index results. The lower the value indicates smaller air pollution. (Left: India, Right: Australia)

This work also provides a variety of machine learning methods, which created different models for the prediction of the concentrations for each pollutant one week later. This is important, because in the near future a model like this can be used for the estimation of the benefits from the replacement of petrol and oil vehicles, with other environmental friendly vehicles.

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