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REVIEW PAPER

Artificial Intelligence Models and Association of Air Pollutants and Novel Coronavirus: A Survey for Asia and Oceania

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Abstract

The Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) pandemic has led to approximately 704 million confirmed cases of coronavirus disease (COVID-19) and resulted in approximately 7.01 million fatalities worldwide. The present review examines the applications of Artificial Intelligence (AI) models concerning the COVID-19 pandemic and its correlation with air pollutants. The objective of this review is to identify, assess, and synthesize pertinent findings regarding the relationship between air pollution and COVID-19. Initially, a comprehensive set of 549 articles was screened, resulting in the selection of 38 articles from the study region through two stringent rounds of inclusion and exclusion. Given the limited availability of published literature originating from countries in Asia and Oceania, the authors endeavoured to focus specifically on studies from this geographical area. The analysis primarily centred on contextual keywords, methodologies employed, algorithms utilized, and, notably, the specific air pollutants examined, such as particulate matter (PM) including PM2.5 and PM10, as well as associated meteorological parameters. Our findings indicate that a significant portion of the research is concentrated in China, recognized as the initial epicentre of the COVID-19 outbreak. Additionally, most researchers from Asia and Oceania primarily concentrated on PM2.5, followed by studies on meteorological factors and PM10. This review delineates five prospective research avenues for future exploration. Consequently, this article enriches the existing literature by providing researchers with insights into current studies, thereby enhancing the accessibility of available evidence for decision-makers and proposing a potential research agenda for forthcoming investigations.

Keywords: Systematic review; COVID-19; Air quality; Coronavirus; Artificial intelligence; Machine learning; Deep learning.

1. Introduction

1.1 Research background

The coronavirus disease 2019 (COVID-19) has accelerated the global concern for protecting and improving the health of the public [1]. The virus that causes COVID-19 is Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2; previously known as '2019 novel coronavirus' (2019-nCoV) [2]. The first outbreak was identified in December 2019 in the People's Republic of China (Hubei

Province) [3]. In March 2020, the outbreak of COVID-19 was declared a pandemic by the World Health Organization (WHO) based on globally growing case notification rates. Unfortunately, there are currently approximately 530 million confirmed COVID-19 cases and 6.29 million deaths globally (World Health Organization (WHO)).

The COVID-19 mortality rate is dependent on comorbidities, with severe cardiovascular complications and respiratory failure [4]. These are similar to those that are influenced by air pollution giving us compelling reasons to be interested in a potential correlation between the two and the consequences of the viral infection [5], [6]. It is critical to establish the purpose and the extent to which particulates such as PM2.5 (< 2.5 micrometres (μm)), and PM10 (diameter 2.5–10 μm) play in the increase and fatality, of the virus.

The burning of fuel is directly associated with Greenhouse Gas (GHG) emissions into the environment; hence, all economic activities that require fuel combustion could be considered significant contributors to global pollution [7], [8]. Air pollution levels in the world's most densely populated cities have reached dangerously high levels, putting the population's physical health at risk [9], [10]. In today's metropolitan regions, principal pollutants, such as methane (CH4), nitrogen dioxide, (NO_2) carbon monoxide (CO), sulfur oxides (SOx), as well as secondary air pollutants like ozone (O_3), nitrogen dioxide, (NO_2), and sulfur trioxide (SO_3) have all increased consistently [11].

1.2 Literature review

It is essential to look at the reported literature on the relationship between the COVID-19 lockdown, air pollution, and machine learning (ML)/deep learning (DL) techniques. Discussing the importance of studies conducted in shortlisted countries such as Korea, the authors discussed the application of the Principal Component Analysis (PCA) filter to DL and how the resultant model could overcome the problems related to the current country program emphasizing predicting or forecasting PM, especially PM2.5 [12], [13].

Eight different research works conducted in India focused on varied ML methods and three on DL methods. The author of the study took an Indian case study that utilised DL with remote sensing during the pandemic and noticed changes in PM2.5. The results showed that the hybrid method i.e., (MLR-ANN) outperformed with the highest accuracy for the prediction of PM2.5 [14]. A comparative study from January to June 2020 was conducted on predicting PM2.5 levels using the LSTM model [15]. A variety of LSTMs was considered in the study from Regression to regression with time steps, to memory between batches and stacked LSTMs. A long-term time-series pollution forecast using statistical and DL methods was done [16]. To forecast the future PM2.5 and PM10 values, historical data and a quantitative approach were carried out. Recently, the association between air pollutants and COVID-19 confirmed cases using DL [17]. Also, researchers studied the impact of the COVID-19 pandemic on air pollution: A global assessment using ML techniques [18].

Analysis of AQ Index in India: pre & post-COVID pandemic was considered using efficient ML approaches through logistic regression and decision tree algorithms [19]. The study found that the major pollutants like PM2.5, PM10, and NO_2, showed a significant reduction during the social distancing period, compared to the same period in previous years [16]. It highlighted several DL methods such as Convolutional Neural Network-Long short-term memory network (CNN-LSTM), LSTM, and DBN to focus on the prediction of air quality [20], [21], [22]. LSTM was also used to predict AQ in Delhi, focusing on the COVID lockdown [23]. The study showed that there was an unprecedented deterioration of air quality after the full lockdown. The study used a variety of LSTMs for univariate and multivariate modelling. The only Indian research that focused on ML models was where PM2.5 was predicted in the lockdown during the pandemic in Kolkata city with the help of MLR and ANN models. This research signifies the importance of the nonlinear model and its precise prediction of PM2.5 over the study area in comparison to the linear model [24].

Studies in Bangladesh showed the potential of several hybrids (ANN and SVM with ARIMA) and

Figure 1: *Illustration of the continents considered for the study.*

standalone algorithms such as decision trees and CatBoost filters for the forecasting of PM2.5 [25]. Also, explanations were shown for the overall prediction, calculations, and meteorology impact of coronavirus using neural networks. The study showed the importance and efficiency of DL models for predicting PM2.5. Another study discussed the impact of COVID-19 through 5 different DL networks. The researchers noticed that certain atmospheric factors such as humidity, temperature, and sun hour have a considerable role (85.9%) in spreading the coronavirus [26]. They also noticed a >90% effect on mortality with COVID-19 as the humidity had an 8.09 % impact on death. The researchers in Jakarta predicted air quality during the COVID-19 outbreak using LSTM [27]. The results obtained show that the Adam optimiser could have brought the results closer to the dataset used. Studies in Jordan assessed and predicted AQ in northern Jordan during the lockdown due to the COVID-19 virus pandemic using ANN [28]. Results of the research indicated a structured and trained artificial neural network could be a productive architecture to forecast parameters of AQ adequate preciseness. The concentrations of several pollutants deteriorated during the period of COVID-19 with varying results. Of the pollutants that are studied, nitrogen dioxide has the most deterioration at 72%, however, particulate matter 10 has a minimum deterioration of 29%. It is observed that the maximum number of research papers (n=17 or 53%) have been conducted in China. All 16 studies [11, [29–44] focused on particulate matter 2.5 algorithms. None of the Chinese researchers used filters [45]. Out of 24 ML algorithms used, random forest (RF) was most widely used in several papers (7 of 16 studies or 47%). ANN was used in 27% and 9 (or 60%) papers using DL algorithms with LSTM being widely used (20%) followed by CNN (20%), BiLSTM, LSTMReg, CVAE, GRU, CLSTM, and CGRU (6%). In Oceania, we have 3 studies from Australia that mostly focus on ML, with RF being the most preferred algorithm (11 times) followed by Others

(2 or 50%), DT, CNB/BNB, SVR, ANN (1 or 25%) [46], [47], [48]. There are two studies at the time of publishing from New Zealand by the same author that also used RF as the choice [49] of modelling (Figure 1).

It is worth highlighting the significance of this topic from a global aspect. Based on the survey conducted on the Scopus database, 70 research articles were published in this research domain. Using the VOSviewer algorithm, a graphical map for the major keywords of those research was presented in Figure 2-3, 914 and 227 keywords occurrence, respectively. Figure 2-3 exhibited 12 research clusters and majorly focused on the COVID-19 lockdown, air pollution, forecasting/predictive models, and environmental monitoring. Whereas, figure 3 is more relatively focused on two occurrence keywords with a total number of keywords 227. Where seven clusters of "research domains" were observed mainly COVID-19 lockdown, human health, and air quality/air pollution. In general, figures 2, 3, and 4 revealed the significance of this research topic although all that research was established within a very short period of 2020-2021.

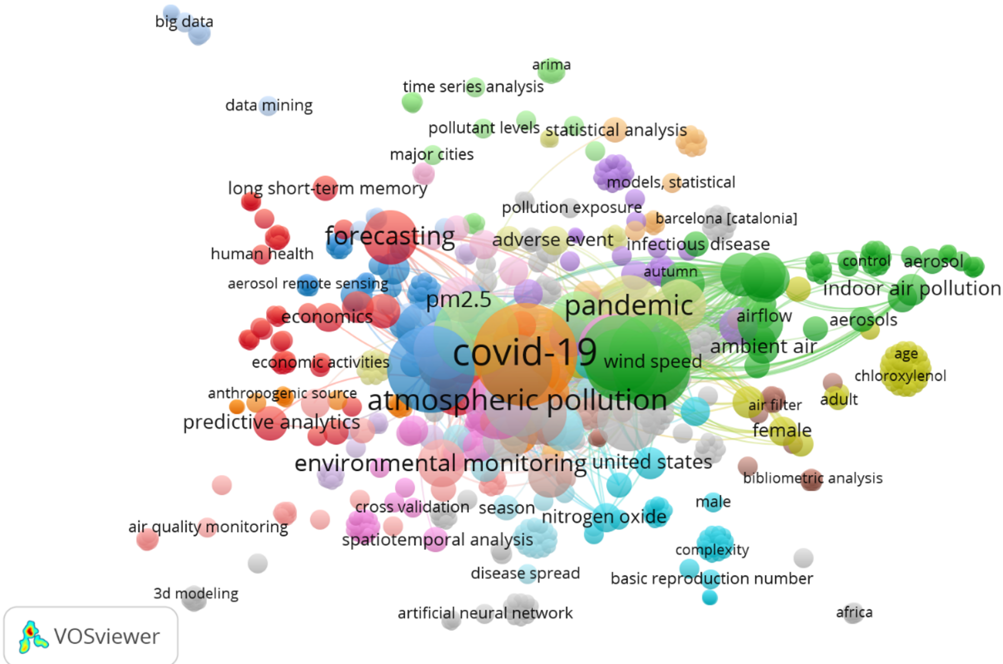

Figure 2: *The major research keywords adopted on the influence of COVID-19 lockdown and air pollution with the collection of 914 keywords.*

Given the significant differences in the extent of COVID-19 transmission globally, it would be worthwhile to evaluate the potential role of air pollution as a contributor to COVID-19 mortality [50]. As such, several outstanding studies have been published recently on a variety of cases involving several kinds of pollution, including England [51], the USA [52], Spain [53], China [54], Vietnam [55], India [56], South Africa [57], and several other countries [58]. These empirical studies found a substantial link between air pollution and COVID-19 cases or fatality, indicating that poor air quality contributes to COVID-19 death. This conclusion is consistent with the scientific literature that suggests that air pollution has an impact on the spread of several viral diseases [59], [60]. The basic idea is that a specific particle concentration can promote COVID-19 and make the respiratory system more vulnerable to infection. In reality, airborne particles could carry infections, making viral infections even more dangerous.

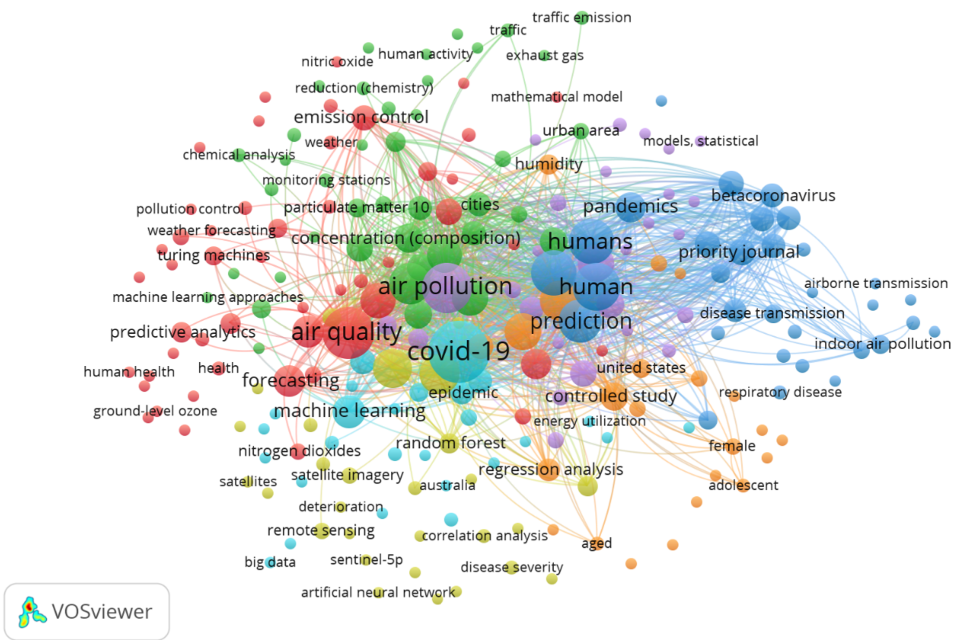

Figure 3: *The major research keywords adopted on the influence of COVID-19 lockdown and air pollution with the collection of 227 keywords.*

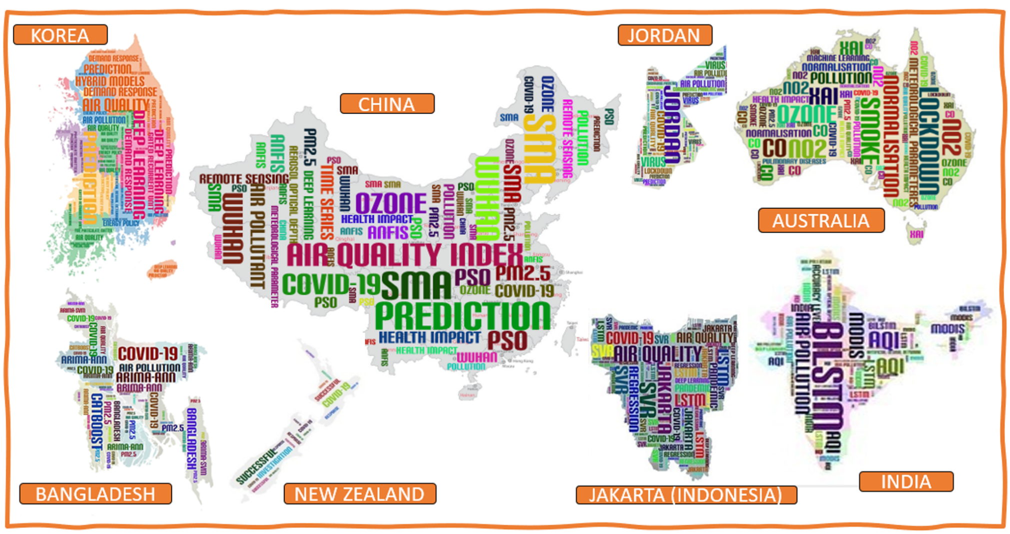

Figure 4: *Word cloud showing the prominent keywords of the specific research undertaken by Asian and Oceania countries shortlisted in this paper.*

Table 1: *The description of the Literature review based on Geography (*=Total studies, =Acronyms).*

Country	Ref.	Based on	Duration	PM2.5	PM10	Meteorological	Findings
India	[14]	A case study focusing on remote sensing and DL in COVID 19. Predicting and estimating changes in PM2.5	Jan 2019 to Apr 2020	Yes	No	Yes	Reduction of 26% in PM2.5 in comparison to pre-lockdown.
	[15]	Comparative Study on Predicting PM2.5 Levels Using LSTM Models	Jan 2020 to Jun 2020	Yes	No	Yes	A comparative study to predict PM2.5
	[19]	Before and after analysis of AQ index through ML in COVID for India	Jan 2015 to Dec 2020	Yes	Yes	Yes	Analyses AQ during pre- and post-COVID days
	[16]	DL and statistical analysis for the forecast of long-term pollution	Jan 2020 to Dec 2020	Yes	Yes	Yes	A comparative study to forecast pollutants
	[22]	Deep Learning Techniques for Air Pollution	Jan 2020 to Dec 2020	Yes	Yes	Yes	CNN-LSTM is proposed as a popular model
	[23]	Usage of LSTM on AQ of Delhi in the lockdown (COVD 19)	Jan 2019 to May2020	Yes	No	Yes	BiLSTM model provides the best predictions
	[24]	Using ANN and MLR models to predict PM 2.5 in COVID in the city of Kolkata	Mar2020 to May2020	Yes	No	Yes	Compare the accuracy of models
	[27]	Increase and spread of AQI and the impact of dual lockdown	Jan 2020 to Jun 2020	Yes	No	Yes	Rise of air quality level predicted
	[17]	Seeking of Association between Air Pollutant and COVID-19 Confirmed Cases Using Deep Learning	Jan 2020 to Jun 2020	Yes	No	Yes	LSTM is most effective to invesitgate the association between air pollutants and COVID-19
	[18]	The impact of the COVID-19 pandemic on air pollution: A global assessment using machine learning techniques	Jan 2020 to Jun 2020	No	No	Yes	Subsequent reduction in O3 for many countries
Bangladesh	[25]	Forecasting PM2.5 in Bangladesh with CatBoost, DT, Hybrid ARIMA with SVM and ANN	Jan 2013 to May 2019	Yes	No	No	Suggests using DL for predicting PM2.5
	[26]	NN and analysis of correlation of weather and COVID 19	Jan 2020 to Aug2020	No	No	Yes	Weather holds 85.88% impact on COVID19
Korea	[12]	Forecasting Models for Predicting PM2.5 with DL and PCA	Jan 2015-to Dec 2019	Yes	No	Yes	PCA in DL can lead to Improvements
	[13]	Demand response in Korea through PM Forecasting by DL and fuzzy inference	Jan 2020 to Feb 2020	Yes	Yes	Yes	The model solves DR programs loopholes
Indonesia	[27]	Prediction of air quality in Jakarta during the COVID-19 outbreak using LSTM	Jan 2020 to Jun 2020	Yes	Yes	Yes	Predict air quality with LSTM
	[45]	The Impact of the Wuhan lockdown on Air Pollution and Health: ML and Augmented Control Approach	Jan 2014 to Feb 2020	No	Yes	Yes	(NO_2) reduction calculation by 63% from the pre-lockdown level

Japan	[28]	Assessing and predicting AQ in northern Jordan during the lockdown due to the COVID-19 virus pandemic using ANN	Jan 2019 to Mar 2020	Yes	Yes	Yes	Structured ANN can be a useful tool
China	[29]	ANFIS model for forecasting Wuhan City AQ and COVID-19 lockdown	Jun2016 to Jun 2020	Yes	No	Yes	Decreases in PM2.5, (CO_2), (SO_2), and (NO_2).
	[40]	Story of environment and people interaction on PM2.5 with COVID 19	Jan 2020 to Mar 2020	Yes.	No	No	COVID-19 decreased the PM2.5
	[32]	Deep-AIR: A Hybrid CNN-LSTM Framework for AQ Modeling	Dec2018 to Mar 2020	Yes	No	Yes	Air pollutants can model disease transmissibility
	[43]	Prediction of Air Quality in Major Cities of China by Deep Learning	Jan 2015 to Dec 2019	Yes	Yes	Yes	Meteorology is the best estimator for (NO_2) and PM2.5
	[41]	Hubei area deaths and evidence from Neural Networks: Covid19, economic growth, and air pollution nexus	Jan 2020 to Jul 2020	Yes	Yes	Yes	Strong relation between PM2.5 and COVID-19 deaths
	[44]	Anomalies generated by COVID 19 with unsupervised PM2.5	Jan 2017 to Feb 2020	Yes	No	Yes	CVAE detection discerns abrupt changes in PM2.5
	[36]	ML in the Yangtze River delta: ambient variations and estimates of PM2.5 during COVID-19 Pandemic	Jan 2019 to Feb 2020	Yes	No	Yes	Estimating PM2.5 decrease in the area of Yangtze river
	[37]	ML models and satellite data: estimating the Impact of COVID-19 on the PM2.5 Levels in China	Nov 2018 to Apr 2020	Yes	No	Yes	ML estimated spatiotemporally PM2.5 and the level was lowered by 4.8 µg/m3
	[38]	Air pollution in central and eastern China based on ML in COVID-19 Lockdown	Jan 2018 to Dec 2020	Yes	Yes	Yes	All the measured pollutants of the study were reduced by 16.4%, 24.2%, and 19.8%
	[33]	ML insights and covid-19 effect in air pollutants: future control policy	Jan 2015 to Dec 2020	Yes	Yes	Yes	PM 2.5, PM 10, (SO_2), (NO_2), and CO lowered by 39.4%, 50.1%, 51.8%, 43.1%, and 35.1%
	[36]	Review on ML in COVID-19, AQ, and Human Mobility	Jan 2020 to Dec 2020	Yes	Yes	Yes	Significant improvement on AQ in COVID-19 lockdown
	[79]	Four-Month Changes in AQ during and after the COVID-19 in China	Jan 2020 to Apr 2020	Yes	No	Yes	(NO_2) lowered by 3653%. PM2.5 was also reduced.
	[31]	Understanding the Impact of transferable models on AQ in lockdown: A technical report	May 2020 to Feb 2021	Yes	Yes	Yes	The only study to use transfer learning to fit variables considered
	[30]	Spring Festival and COVID-19 Lockdown: Disentangling PM Sources in Major Chinese Cities	Jan 2015 to Dec 2020	Yes	Yes	Yes	15.4%, 17.0%, 14.5%, 7.6%, 9.7%, and +24.6% changes for (NO_2), (SO_2), CO, PM10, PM2.5, O3
	[42]	Sources in Major Chinese Cities Impact of the COVID-19 Event on Air Quality in Central China	Jan 2017 to Dec 2019	Yes	Yes	Yes	PM2.5 (72.0%), O3 (16.4%), PM10 (8.3%), (NO_2) (2.9%), CO (0.4%)

	[39]	COVID-19 and air pollution and meteorology-an intricate relationship: A review	Jan 2020 to May 2020	Yes	Yes	Yes	Significant reduction in PM10, PM2.5, BC, NOx, (SO_2), CO and VOCs
	[37]	Importance of meteorology in air pollution events during the city lockdown for COVID-19 in Hubei Province, Central China	Jan 2000 to Dec 2020	Yes	No	No	Substantial contribution to PM2.5
Australia	[48]	Megafires in black summer of 2019-2020 and AQ's health impact with Sydney and Melbourne COVID-19 lockdown	Jan 2019 to Oct 2020	Yes	Yes	Yes	Significant increases of O3, CO, PM10 and PM2.5
	[46]	COVID-19 lockdown effect in Sydney's AQ	Apr 2020 to Jun 2020	Yes	No	Yes	(NO_2), CO, and PM2.5 decreased, O3 increased
	[47]	Whether the weather will help us weather the COVID-19 pandemic: Using ML to measure Twitter users' perceptions	Jan 2020 to Jun 2020	No	No	Yes	40.4% uncertain about weather's impact, 33.5 % no effect, and 26.1 % some effect.
New Zealand	[49]	Response with the investigation to COVID 19 and weather impact on NZ air quality	Dec 2018 to June 2020	Yes	Yes	Yes	ML found good R for (NO_2); Modelling results were weaker for coastal particulate data
	[50]	An investigation of the impacts of a successful COVID-19 response and meteorology on air quality in New Zealand	Jan 2020 to Dec 2020	No	No	Yes	Changes to air quality under COVID-19 restrictions were compared with machine learning estimates (ML)

As particulates have a considerable emissions footprint [61], [62]. The potential role of PM in spreading COVID-19 was researched in the first evidence-based research hypothesis [63]. Afterwards, the authors researched the significant correlation between the mortality of COVID-19 and air pollution [64]. Their results showed that PM pollutants were the reason for 17% of mortality (North America), 27% (East Asia), 19% (Europe), and overall, 15% (worldwide). Since then, several studies have discussed the potential link between PM and COVID-19 and showcased their correlation [61], [65]-[68].

Based on the listed research in Table 1, it was observed that most research was conducted with at least 6 months of data for research. However, some studies, such as those from India, used 6 years of data from Jan 2015- Dec 2020 [19]. The research was on the before and after the pandemic's effect on AQ in India using machine learning. Research in Korea [12] used 5 years of data from Jan 2015 to 2019 and proposed PCA to DL forecasting models for predicting PM2.5. Seven years is the maximum duration of data from a study in Bangladesh from Jan 2013 to May 2019 [25]. The study uses several models, such as CatBoost, and decision tree amongst others to forecast Atmospheric PM2.5. In Australia, the mega-fires of 2019-20 and their impact on air quality were studied with the effect of the COVID-19 lockdown in the cities of Sydney [69]. Over 2 years of data from Jan 2019-Oct to 2020 was used in the study. Overall, 18 studies took more than 1 year of data, and 15 studies were researched in less than 12 months. This review was further segmented based on the various air pollutants forecasted across different continents such as PM2.5, PM10, and Meteorological factors. Out of all studies (n = 38), PM2.5 and meteorological factors (effect of temperature, humidity, greenhouse gases, etc.) seemed to be the most popular choice amongst researchers (n=35 studies or 92%), followed by PM10 with (n=20 studies or 52.6%). At the time of writing this paper, no research was conducted with total suspended particles or visibility-reducing particles with Asian or Oceania data.

1.3 Different sources of transmission of COVID-19

The published literature suggests that there is a large amount of uncertainty around the sources of transmission of COVID-19 [70], [71]. However, the dominant mode of transmission is likely to be airborne [65]. Transmission is more rampant when people breathe in air contaminated by droplets and small airborne particles. The risk of breathing these in is highest when people are nearby, but they can be inhaled over longer distances, particularly indoors. Airborne transmission refers to the presence of microbes within droplet nuclei, which are generally considered to be particles <5µm in diameter and can remain in the air for long periods and be transmitted to others over distances greater than one meter. For COVID-19, airborne transmission may be possible in specific circumstances and settings in which procedures or support treatments that generate aerosols are performed. Furthermore, in many studies, it was reported that there were also infections, where infection spread with health workers using incomplete or inappropriate personal protective equipment, such as the absence of eye protection, and these reports cannot rule out other modes of transmission.

1.4 Importance of developing a systematic review

This article reported on the published literature and discussed the role of air pollutants in the pandemic in 8 countries in Asia and Oceania. These systematic reviews aim to identify, evaluate, and summarise the findings of all relevant individual studies on the association of air pollutants and novel coronavirus with AI models. This will make the available evidence more accessible to decision-makers. It also helps to comprehensively record and assess the state of knowledge in a chosen area. Systematic reviews search, appraise and collate all relevant empirical evidence to provide a complete interpretation of research results. The literature search did not find papers reporting on comprehensive reviews of Asian and Oceania countries and thus the gap that the present authors are trying to fill with systematic review through AI models. Experts have recently focused on a critical environmental issue: the increasing level of small particles (PM10 and PM2.5) in big cities [72]. These particles are mostly sourced from factories and home heating. Generally, the principal source of pollution causes specific health problems for city dwellers [73]. Over the past few decades, particulates have been steadily increasing in urbanized regions with increased road traffic and hence the need for more petroleum fuels (gasoline & diesel) [74], posing a threat to human health [75]. It is a major cause of traffic congestion, prolonged travel time, and excessive fuel consumption and carbon emissions while preventing efficient travel [76]. A serious issue about PMs is that they are responsible for serious health problems in the community, such as respiratory infections, lung cancer, asthma, chronic obstructive pulmonary disease, etc. [77], [78]. These particulates last longer in the air than the bigger particles due to their small weight and size; they can also easily infiltrate the human lungs and circulatory system [79]. As a result, Mayors of most large cities in Asia have made improving air quality a top priority. This problem has recently become more prevalent in several places throughout the world. No other measure comes close to the COVID-19-related lockout. Interestingly, one unintended consequence of the lockdown during COVID-19 is a great reduction in both emissions (primary and secondary), casting doubt on the long-established link between human activity and air quality.

1.5 Research objectives

To address the literature gaps, the research objectives are as follows:

1. This study reports on research that explores the robustness and potential of artificial intelligence techniques of ML and DL for the objectives considered in the study.
2. The research investigates the published literature comprehensively with all-inclusive applications of ML and DL in detecting the correlation between COVID-19 and forecasting air quality potentially for Asian and Oceania countries.
3. The authors suggest recommendations for further studies after reporting on the review in the context of the usage of algorithms in fighting the COVID-19 pandemic.
4. Finally, the future research opportunities are summarised at the end of this paper.

The remaining systematic review has been organised as below. Section 2 explains the Study design strategy with which this review has been conducted. It also discusses the findings and data analysis. Section 3 highlights the Results and Discussion. Furthermore, the Conclusion is presented in Section 4 while the possible opportunities for further research to fight COVID-19 by targeting air pollution with deep learning and artificial intelligence with final remarks, shortcomings, and possible suggestions can be found in Section 5.

The Appendix shows a list of prominent COVID-19 Datasets used by works considered in this study, an illustration of the continents considered, and a word cloud showing the prominent keywords of the specific research undertaken by Asian and Oceania countries shortlisted in this paper.

2. Study design (Materials and Methods)

This section deals with the materials and methods, i.e. the design of the study, and analysis of the data.

2.1 Sample and data

Out of the selected literature considered for Asia and Oceania 33 full-text eligible articles for Asia, 2 were from Korea (5.2%), 10 from India (26.3%), 2 from Bangladesh (5.2%), 1 from Jakarta (2.6%), 1 from Jordan (2.6%), and 17 from China (44.7 %). From Oceania, we had 5 articles, of which 3 were from Australia (60%) and 2 from New Zealand (40%). All these articles were published as original research. The time frame of all research conducted was after Jan 2020. Out of 38 articles combined in the study, 37 (97%) articles were published in academic journals, while one (i.e., 3%) article was archived as a pre-print. All the articles (100%) were original research.

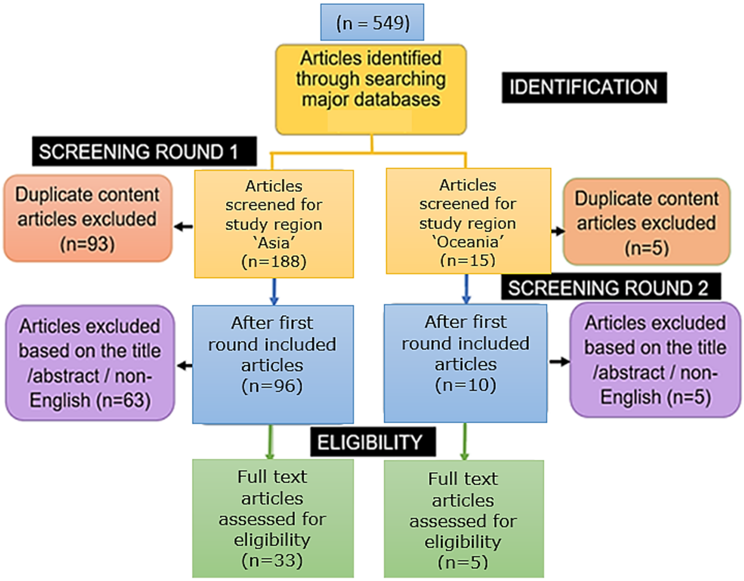

Figure 5: *Systematic selection of studies and flowchart based on PRISMA.*

2.2 Methodology and data analysis

For this study, the authors have adopted a methodology strategy as discussed in [**81**] which consists of:

1. Identification stage – Search approach
   Potential databases such as IEEE Xplore, PubMed, Google Scholar, and Springer Link were searched for related articles. Important keywords like 'COVID-19', 'pandemic' 'CoV2' or 'Coronavirus' along with 'air quality, 'air pollutants', 'particulate matter' and key phrases: 'machine learning, 'deep learning, and 'artificial intelligence' were searched. Then the combination was searched with the names of the continents Asia' and 'Oceania'. e.g. ('pandemic AND deep learning OR machine learning' AND 'COVID-19 OR CoV2 OR coronaviruses AND Asia OR Oceania').
2. Screening rounds 1 and 2- Criteria for inclusion or exclusion
   Primarily the articles were screened (a) based on study region i.e., Asia and Oceania. (b) Duplicate content articles were screened. That means articles that study similar purposes and consider a similar set of data. Then, in the second round (c), articles were excluded based on the title, abstract, or non-English content. Special care was taken to select only those articles that used AI models and developed algorithms to forecast air pollutants in the ongoing pandemic.
3. Eligibility
   Around 549 articles were selected from the targeted databases. Figure 5 illustrates the procedure undertaken with different stages. After the completion of the identification round, 185 articles were selected for the Asian continent and 15 for Oceania. 93 articles were excluded with duplicate content as mentioned in the above Stage. Five articles were excluded with duplicate content for Oceania. From 188 articles we were left with 96 articles after the first round for Asia, and 10

articles for Oceania. Screening round 2 helped in further filtering as 63 articles were removed based on title or irrelevant abstract or if they were not written in the English language. Similarly, from 10 articles for Oceania, 5 were removed for similar reasons. In the end, 33 full-text articles were assessed for eligibility for Asia and 4 for Oceania.

4. Extraction of data

   After meticulously assessing the eligible articles, the next stage was to extract relevant data involving various DL and ML for our objective of forecasting air pollutants. This was essential to check what relevant algorithms and techniques were used by the researchers in Asia and Oceania. This also helped us to understand the implications due to the pandemic of COVID-19 and forecasting air pollutants.

   From the selected articles, the research data was extracted primarily related to the name of the continent/country where the study was conducted, the title of the research, the duration of the study, the air pollutant and meteorological data used in the study, name of ML or DL technique used, and keywords. In the end, the data collected helped in condensing the published literature and in recognizing the future scope. Table 1 shows the result in the form of a key description of the selected reviewed studies based on Geography.

3. Results and Discussions

3.1 Techniques used to forecast air pollutants

Appendix A showed the compilation of all machine and deep learning algorithms considered (in blue) in the study. The optimal algorithm of each article is shown in red. Of all the ML algorithms considered across both continents (m=26), 4 articles (15%) considered the filter i.e., CatBoost, Principal component analysis (PCA), Particle swarm optimisation (PSO), and Ridge Classifier (R.Classifier) in the study along with other approaches. Interestingly, only Ridge Classifier was used in Oceanian studies and PCA in Asian studies (twice).

Of all the ML algorithms, RF (Random Forest) seems to be a popular choice for modelling, which occurred 11 times (or 34%) followed by ANN (Artificial Neural Network) (n=10 out of 38 or 26.3%). The next preference seems to be DT (Decision Trees), 5 or 15% followed by SVR/SVM (Support vector regression/ Support vector machine) (n=4 or 14%) of which 1 occurrence is in the study based on data in Australia (Oceania). k-NN (k-nearest neighbours) and SMA (Slime mold algorithm) are used thrice or 9%, followed by MLP (Multilayer Perceptron), ARIMA (Autoregressive Integrated Moving Average), Others (Linear regression with gradient, Support Vector Machine with Gradient Descent, InceptionV3, and Resnet50) that were individually used once. ANFIS (adaptive neuro-fuzzy inference system), MLR (Multiple linear regression), MH (Meta-heuristics), and Bayesian were also used once. There were hybrids such as MLR-ANN (MLR-Artificial Neural Network), ARIMA-SVM, MLP-Fuzzy Inference, CNB/BNB (Complement Naïve Bayes/ Bernoulli Naïve Bayes), and PSO-SMA-ANFIS are all used only once in the studies.

From (d=14) DL algorithms, the most popular modelling choice across Asia and Oceania was LSTM with 13 occurrences (or 93%), followed by BiLSTM (bidirectional LSTM), and CNN (convolutional neural networks) with 5 occurrences (36%). EDLSTM (Encoder-Decoder LSTMs), CLSTM were used 4 times (29%), GRU (gated recurrent unit) 3 times (21%), and LSTMReg (LSTM Network for Regression) 2 times. The least used algorithms in the study across continents were NLP (Natural language processing), GCN (Graph Convolutional Network), CVAE (conditional variational autoencoder), LSTMB (LSTM with Memory Between Batches), SLSTM (Stacked LSTMs) with hybrids CGRU, and PCA-LSTM being used only once.

3.2 Discussion of the data used

Nine studies (28%) used satellite-derived data for calculations and 72% used different types of data, including text and images, to corroborate their findings, as shown in Appendix A. Many studies did not take much data for the research due to the ongoing pandemic situations and many took multiple weather variables for their research, which may have caused some issues. Researchers discussed the issue of dimensionality problem. They observed the problem with a smaller number of observations [12]. They researched 5-year data collected at the daily temporal horizon in 8 cities in Korea. Also, a fuzzy inference engine with MLP proposed in another Korean study in Seoul alleviated the problems of the current demand reference program [13]. This study based its findings on the data of meteorology for PM2.5 and PM10 prediction. However, the missing data for the pollutant(s) or meteorology creates uncertainty in the model which should be treated using appropriate statistical descriptors.

The authors of the study conducted in India established their research based on remote sensing data [14]. Another study collected a variety of real-time data and exploratory variables at 15-minute intervals to apply ANN and LSTM to compare predictions [80]. This involved pre-processing and cleaning to have a more ordered dataset to avoid any inaccuracies. One of the studies that took the longest duration of data was to measure the pollution level based on greenhouse gases such as Sulfur dioxide (SO_2), Nitrogen dioxide (NO_2), Carbon monoxide (CO), Ozone (O_3), PM2.5 and PM10 [19]. Researchers carried long-term forecasts and compared the efficiency of DL models in the pre and post-COVID era [16]. The limited data availability may cause less robust techniques such as basic statistical techniques like Holt-Winters to surpass robust AI models. This can be avoided by increasing the quantity of data or if the formulated model can predict the daily/monthly time horizon, based on past data. This will result in a better and a reliable model.

3.3 Associated problems in the COVID literature

Careful observation in our study reveals that the papers on both continents have not considered exogenous variables. This means the absence of all such variables whose value is determined outside the model. The authors see this as a shortcoming, and their inclusion could have increased the preciseness and computational efficiency of the models designed. Researchers discussed the need for more data and the importance of Spatio-temporal information while predicting air pollution in the COVID era [23]. The study collects spatiotemporal data of PM2.5 to obtain remote sensing integrity with the increased accuracy of data [24].

There were reports about efforts to overcome the limitations of traditional hybrid methods; researchers used image data with the DNN as a time and labour-saving solution [26], and research eliminated strong assumptions such as prediction shifts caused by gradient bias [25]. Table 2 lists prominent COVID-19 datasets used by works considered in this study.

The literature has revealed certain limitations in the observed relationship between COVID-19 and PM2.5 pollution; however, this is not enough to establish a causal relationship. Even with powerful AI models, disentangling the impacts of strongly correlated parameters is difficult and not always possible. It's difficult to distinguish between pollution's direct consequences and the indirect effects of things like economic and racial inequality. Another issue is determining the appropriate proxy (or proxies) for the frequency of interactions between people in a given society, even as the human-to-human form of transmission is undeniably the most prevalent in COVID-19. Considering this, some scholars have correctly emphasised the need for an accurate assessment of the movement of the target population [81], [82]; they have also recommended possible proxies, ranging from specific economic measures and commercial interactions to account for the number of investors or job seekers; analysis of public transportation-related statistics has also been suggested. While identifying and finding additional variables that accurately reflect these factors is difficult in a unified and systematic manner across all the studied regions, there is still room for improving the adopted methodologies in this regard.

Table 2: *A list of prominent COVID-19 Datasets used by works considered in this study.*

Resources	Link	Details
AitsLab Corona	Aitslab/corona	NLP toolbox for COVID-19 NLP research.
Amazon AWS	aws.amazon.com/covid-19	A case study focusing on remote sensing and DL in COVID 19. Predicting and estimating changes in PM2.5
India	aws.amazon.com/covid-19	Public repository for COVID-19 data analysis.
Australia	australia.gov.au/	Official repository of Australian state and territory COVID-19 figures.
Bangladesh	dghs.gov.bd/index.php/en/home/5343-covid-19-update	Directorate of Health Services, COVID-19 dashboard of Bangladesh.
BSTI Imaging database	bsti.org.uk/training-and-education/covid-19-bsti-imaging-database/	British Society of Thoracic Imaging Covid 19 CT scans data.
CORD-19	semanticscholar.org/cord19	Open research database and a free resource for over 52,000 scholarly articles.
COVID-19 Graphs	worldometers.info/coronavirus/worldwide-graphs/	This repository gives the tools to visualize the various statistics of COVID-19 using case data.
HARVARD Dataverse for China	dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/MR5IJN	Harvard Repository of China's COVID-19 statistics.
India	mygov.in/covid-19/	Government of India's repository of COVID-19 cases.
Jakarta	corona.jakarta.go.id/en	Jakarta official webpage of COVID-19 cases.
Kingdom of Jordan	corona.moh.gov.jo/en	Reports and COVID-19 statistics of Kingdom of Jordan.
LitCOVID	ncbi.nlm.nih.gov/research/coronavirus/	Curated literature hub for tracking 2019 novel Coronavirus.
MONTREAL.AI	montrealartificialintelligence.com/covid19/	A resource to use with deep reinforcement learning.
NIH NLM LitCovid	ncbi.nlm.nih.gov/research/coronavirus/	Curated literature hub for tracking up-to-date scientific information about COVID-19 with central access to relevant articles in PubMed.
Republic of Korea	ncov.mohw.go.kr/en/	Repository of case statistics of Korea.
UN Humanitarian data exchange	data.humdata.org/	United Nations OCHA Humanitarian Data Exchange Project.
World Health Organisation (WHO)	covid19.who.int/	WHO Coronavirus (COVID-19) Dashboard.

The possible disparity between interior and outdoor air pollution is another methodological barrier that is difficult to overcome. This is the case because people are reported to spend an average of 80-90% of their time indoors [83]. As there are no systematic data sources on indoor pollution, we must make the logical assumption that indoor and outdoor pollution is substantially associated in general [84]. Also, there is an inescapable trade-off between selecting an analysis scope that exhibits severe levels of air pollution on the one hand and the need for consistency in the other parameters [85], [86], [87]. This study is focused mainly on Asia and Oceania due to the highly polluted environment of the regions which are considered above health-hazard limits. As a result, the COVID-19 context has a significant impact on air pollution, particularly in places like Delhi, Bangkok, Kuala Lumpur, Beijing, and Sydney. Owing to this fact, the research progress on the linkage between the air quality indicators and the COVID-19 transmissibility [88].

It's fascinating to think about random parameters when evaluating air quality. The significance of meteorological parameters such as temperature, humidity, and UV radiation on the transmission of SarS-CoV2 for example, may be less than usually anticipated based on the major predictors. Even though there are compelling arguments that high humidity and temperature levels limit virus transmission [89], [90], there are also compelling arguments that they have no impact on the rate of virus transmission. It is worth noting that the literature has not entirely agreed on this hypothesis as there are contrary views about it [91], [92]. Despite the emphasis on the impact of meteorological conditions in this review, some scientists dispute that weather elements have a substantial impact on the transmission of COVID-19 [93]. It is important to highlight, however, that fluctuations in meteorological conditions are significantly larger on a worldwide scale, especially where these elements have a greater impact.

4. Conclusion

This manuscript examined 549 selected scientific articles focused on Asia and Oceania. These articles narrowed their research on COVID-19 and air pollution and finally, 38 papers were shortlisted that used AI models for the considered objective of forecasting air pollutants. Computer aid models are an active and evolving research field, particularly in atmospheric sciences. Despite the rapid advancement and popularity over the past years, the usage is noticed to have been limited to the continents of North America and Eurasia. In comparison, fewer studies have been conducted in Asia and particularly the Oceania continent.

We noticed a few important points through this systematic review-

- This systematic review shows that most research papers focused on forecasting or predicting the number of air pollutants. The literature that revolved around primarily the concentration generally took an ensemble of algorithms or simply algorithms based on regression. This may be because this choice helped in an acceptable arrangement between the model performance and analysis of results.
- All these articles focused on forecasting through ML and DL techniques and prioritised accuracy over interpretability.
- Forecasting contaminants such as particulate matter is particularly challenging. The chaotic behaviour of air pollutants creates major difficulties in tracking their three-dimensional movement. Besides, in tropical climates high variations of temperature and relative humidity also affect the ambient concentration of particulate matter. This might be the reason for the choice of these robust algorithms.
- The analysis by the authors reveals that the extent of the forecasting accuracy is lesser as compared to that of the models that used estimation. The 3-D chaotic nature of air pollutants may demand the application and better-suited computationally efficient algorithms such as DL. This may enable us to take care of the complexity of forecasting future contaminants.

- The preciseness of ML for particulate matter prediction and forecasting got to maximum numbers compared with the other pollutants. In general, it was observed that the preciseness of peaks with a higher pollution rate was lesser than the low or medium pollution peaks. Furthermore, the forecasting result was constrained to meteorological contaminants like CO with Nitrogen oxides (NOx). Moreover, the models seemed to behave superior for weather that was extreme such as windy, snowy, and fall to name a few.

5. Limitations and future research

This section presents the limitations and scope of further research opportunities on Air pollutants and ML/DL benefits but is not limited to the COVID-19 pandemic.

- Usage of a large dataset and removal of dimensionality
  The availability of large and different types of data such as texts, images, spatiotemporal, and remote sensing data will assist in conducting several experiments and applying a range of modelling algorithms. This can result in improved performance. It would also assist in a general yet ordered and validated result, helping in the pandemic research. However, the parsimony of the model should also be taken into consideration because the parsimonious model presents the 'greatest' explanation or predictive power with the least 'parameter' and 'process' complexity.
- Enhanced focus on air quality and Deep Learning
  A few research that considered the majority of the parameters of air pollutant forecasting, pandemic, and Deep or Machine Learning algorithms have been published from the selected continents. However, further research can be carried out, particularly focusing on the Deep and Machine Learning algorithms.
- Inaccuracies of greenhouse gas emissions
  Limitations in data availability, especially data without bias or data with high resolution may produce incorrect emissions/concentrations. This may hold for gases, such as CO or O_3. This can create deviations between the model predictions and observations. Therefore, future research should take a top-down approach focused on individual pollutants while developing the models.
- Prior evaluation of the robustness of the models
  An upcoming and active research field with innovative algorithms and methods is ML/DL. It keeps on emerging, resulting in a better and more refined solution. Before formulating a system or approach, the limitations of several available models need to be considered that may provide better responses to uncertainty quantification in predictions.
- The interventions
  The government should focus on various technological or policy-based interventions aimed at stimulating the decarbonization of economic activities. This will offer a long-term solution to containing pandemics like COVID-19, its impacts, and future reoccurrences. A paradigm shift is also necessary acceptance of research, development, & innovations throughout economic sectors. Economic growth can only be decoupled from air pollution by relying on renewable and clean energy sources for economic activities. The promotion of a healthy and clean atmosphere could be a useful factor in reducing the rapid transmission of a pandemic like COVID-19. This study could not reach a consensus result due to the variations in countries across the world, as well as the complexity of COVID-19; however, the adopted empirical procedure in this work laid the groundwork for future research needed to mitigate such pandemics, and future occurrences.
  Therefore, the authors suggest that future articles may take care of further challenges of enhancing the models aiming to forecast air pollution along with episodic events. This study has reviewed the past research carried out for prediction and forecasting through several methodologies during the ongoing pandemic. The relevant literature concerning the issues, challenges, methodology, and real advantages has been presented. The study shows that the appropriateness of methods is dependent on the target dataset. Overall, in comparison to the single algorithms, the hybrid

algorithms performed better and more satisfactorily. Finally, from the analysis of the study, it is noteworthy that harmful and increased contamination concentrations of particulate in the southern hemisphere and the Asia Pacific are understudied when combined with DL or ML models.

Conflicts of Interest

The authors declare no conflict of interest that could have appeared to influence the research conducted in this study.

Credit authorship contribution statement

Ekta Sharma: Conceptualisation, Data curation, Formal analysis, Methodology, Software Validation, Writing – Original draft, Review, and Editing. **Ravinesh C. Deo**: Review, Discussion and Editing. **Zaher Mundher Yaseen**: Manuscript revision, discussion, analysis, and submission of the manuscript. **Mukesh Khare**: Mentorship and Review. **Sachin Dhawan**: Review and Editing. All authors have read and agreed to the published version of the manuscript.

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The manuscript is conducted in the ethical manner advised by the targeted journal.

Consent to Participate

Not applicable

Consent to Publish

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The authors declare no conflict of interest.

Availability of data and materials

All data are reported in the manuscript.

List of abbreviations

SARS-CoV-2 Severe Acute Respiratory Syndrome Coronavirus-2
WHO World Health Organization
COVID-19 Coronavirus disease-2019
2019-nCoV 2019 novel coronavirus
PM10 Coarse particles/Diameter = 2.5-10 Mm
PM2.5 Fine particles/Diameter = 2.5 Mm or less
SVR Support Vector Regression
MLP Multilayer Perceptron
PSO Particle swarm optimization

ARIMA Autoregressive Integrated Moving Average
LSTMB LSTM with Memory Between Batches
LSTM Long Short-Term Memory
BiLSTM Bidirectional LSTM
CNN Convolutional Neural Networks
EDLSTM Encoder-Decoder LSTMs
LSTMReg LSTM Network For Regression
NLP Natural Language Processing
GCN Graph Convolutional Network
CVAE Conditional Variational Autoencoder
CNB Complement Naïve Bayes
ANFIS Adaptive neuro-fuzzy inference system
k-NN k-nearest neighbours
ANN Artificial Neural Network
GHG Greenhouse Gas
WHO World Health Organization
DL Deep Learning
ML Machine learning
PCA Principal Component Analysis
NOx Nitrogen Oxides
SO_2 Sulfur Dioxide
SO_3 Sulphur Oxides
SOx Sulphur Trioxide
NO_2 Nitrogen Dioxide
O_3 Ozone
CO Carbon Monoxide
DR Demand Reference
DT Decision Trees
SLSTM Stacked LSTMs
RF Random Forest
GRU Gated Recurrent Unit
RC Ridge Classifier
BNB Bernoulli Naïve Bayes
MH Meta-heuristics
SMA Slime mould algorithm
SVM Support vector machine

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