Int J Syst Assur Eng Manag (December 2023) 14(6):2208–2217
https://doi.org/10.1007/s13198-023-02050-8

ORIGINAL ARTICLE

Improved deep learning algorithm with innovation perspective: a prediction model of the mortality of respiratory infections

Usharani Bhimavarapu[1]

Received: 5 May 2022 / Revised: 20 June 2023 / Accepted: 17 July 2023 / Published online: 30 August 2023

Abstract Public health is now seriously threatened by the COVID-19 outbreak. COVID-19 infections have spread to most countries, but certain regions have had more infections and casualties than others. It is yet unclear what causes these variances specifically. This motivates us to investigate, the association between air pollutants, metrological indices, and COVID-19 cases and deaths. We collected the daily air pollution, metrological and COVID-19 infected cases data and predicted the respiratory casualty. In this study, we assess the impact of air pollution and the metrological indicators on the respiratory infection casualty. First, we assessed how air pollution and metrological parameters correlate to respiratory infection transmission. Our findings highlight that temperature, wind speed, and particulate matter (PM2.5) positively correlate to respiratory virus transmission. In this study, an Enhanced Regularization Function in the Artificial neural networks (ERF-ANN) model predicts respiratory casualty. The ERF-ANN model was found to have minimal errors when predicting respiratory casualties over the rest. We conclude that respiratory infection transmission prefers low temperatures and polluted air. This system will alert chronic patients early based on their environment, and all disease groups will be notified.

Keywords Air pollution · Respiratory diseases · Influenza · Regularization

✉ Usharani Bhimavarapu
ushareddy@kluniversity.in

1 Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India

1 Introduction

Environmental problems, especially air pollution caused by rapid urbanization, growing factories, and vehicles, affect public health adversely. Individuals' health is negatively affected by air pollution. Air pollution directly correlates with infectious diseases (Luo et al. 2020) and respiratory diseases like Asthma and Tuberculosis (TB) (Gorai et al. 2016; Jiandong et al. 2020). In 1952, the London Smog Phenomenon resulted in almost 12,000 deaths due to atmospheric congestion and increased air pollution concentrations (Lee et al. 2016; Bert and Stephen 2002). The Air Quality Index (AQI) measures air pollution levels (Weichenthal et al. 2014). AQI depends on the average concentration of the particulate pollutant measured over a specific time interval. As AQI rises, the population experiences severe adverse health effects, and a specific color code was assigned to each range of air pollution based on the severity of adverse health effects. The air quality index indicates how polluted the air is and considers the Particulate Matter (PM) concentrations.

The primary pollutant that contributes to air pollution is particulate matter, and a rise in PM concentrations has a negative impact on human health (Strak et al. 2010). There are two subcategories of particulate matter, coarse particulate matter (PM_{10}) and fine particulate matter ($PM_{2.5}$). PM_{10} are particles of 10 µm in diameter, and $PM_{2.5}$ is a fine inhalable particle with diameters generally 2.5 µm. $PM_{2.5}$ is more dangerous than PM_{10} i.e., particles with minute size (< 2.5 µm) can able to travel deeply into the respiratory tract and can cause breathing issues to individuals. It leads to respiratory problems as it remains in the atmosphere much longer. Particulate matter ($PM_{2.5}$) concentrations correlate positively with asthma, pulmonary infections, and pneumonia. It can enter the nose and mouth to deposit on the respiratory tract, and exposure to high $PM_{2.5}$ concentrations may worsen asthma symptoms (Hao and Linyu 2018; Jennifer et al. 2010). There is evidence that $PM_{2.5}$ is causing an increase in asthma among children and elders (Robert and Kazuhiko 2010; Ko et al. 2007).

Respiratory conditions like asthma are impacted by the effects of climate change on air pollution levels (Renato et al. 2010). As a result of ingestion, inhalation, contact, and iatrogenic transmission, pathogens enter the respiratory system. Small virus particles are suspended in the aerosol during dust storms and can travel through the air on airborne particles (Sutyajeet et al. 2016). The influenza virus survives for days on surfaces and for hours in aerosol; 21% of the virus is transmitted through aerosol, 29% by close contact between individuals, and 50% via contact with surfaces (Antonio et al. 1996). Asthma outbreaks are caused by air pollution and meteorological parameters like high temperatures, precipitation, air pressure, and humidity (Iha et al. 2016; Killerby et al. 2018). Multiple viruses are affected by temperature and relative humidity, and influenza infection is inversely correlated with both (Lipsitch 2020).

An investigation has recently been conducted regarding the relationship between particulate matter and communicable disease fatality rates (Yao et al. 2020). Infectious respiratory mortality may be increased by exposure to particulate matter. Pollution partially impacts lung infection-related mortality in Italy as of March 2020 (Conticini et al. 2020). Infectious respiratory diseases are strongly influenced by meteorological conditions. With seasonal variations in meteorological conditions, there is no quantitative association between health risk and air quality index. Temperature parameters such as temperature, perception, virus transmission, and viability are strongly correlated. In addition, the virus transmits more efficiently in winter than in summer (Killerby et al. 2018; Charkraborty et al. 2021). Health disorders affecting the respiratory system still face many challenges, including underdiagnosis and overdiagnosis, high mortality rates, and high costs associated with exacerbations (Exarchos et al. 2020). This study's main objective is to investigate changes in respiratory infections related to particulate matter and respiratory casualty prediction trends.

Traditional models such as Markov chain, autoregression integrated moving average, and regression models have difficulty meeting assumptions, overfitting, and increased loss when predicting respiratory casualty. These models require a long time and complete datasets to obtain unbiased estimates. Analyzing and modeling complex health disciplines has been made possible by deep learning models like artificial neural networks (ANN). These models do not require prior knowledge and are independent of the data's statistical distribution. Using the data released by the Indian government, we attempted to predict respiratory casualty caused by air pollution that adversely affects the human body. An improved deep-learning algorithm was applied to identify respiratory infections caused by various viruses to predict respiratory casualty. The performance of the proposed deep learning algorithm was then verified, and it was compared with existing deep learning algorithms with default regularisation.

1.1 Motivation

Air pollution causes many environmental and health issues, including cardiovascular disease, respiratory disorders, and early death. Anthropogenic activity produces hazardous gases and particles released into the atmosphere, causing emergencies. Humans exposed to air pollution over an extended period are susceptible to lung cancer, asthma, chronic obstructive pulmonary disease, and other respiratory health issues. The accurate predictions will help to give early warnings during hazardous air pollutants. Prediction, tracking, early alerts for hazardous air quality, and preventative measures help manage pollution and improve air quality through environmental regulations and pollution control techniques. These actions also contribute to environmental sustainability. Along with precise air pollution prediction levels, the public and the government may take the necessary actions.

1.2 Research contributions

(1) Applied the enhanced ANN model to estimate the respiratory infection risk.
(2) An improved regularization function is proposed to estimate accurate values and reduce the loss of estimation of the respiratory infection risk.
(3) Extensive Experiments were conducted on publicly available air pollution datasets, meteorological data, and respiratory infection data.

2 Related work

Burnett et al.'s (Burnett et al. 2018) discussion of mortality risk factors focuses on the issues of contact to outdoor fine PM. To calculate and analyse the risk functions while exposed to elevated PM2.5 concentrations in the wide, they use the Global Exposure Mortality Model. Based on the duration of exposure to fine particulate matter, air pollution has a substantial influence in environmental risk factors that cause disability and cardiovascular death (Rajagopalan et al. 2018). Lelieveld et al. (2019) address empirical studies that argue for reevaluating disease trouble by comprehending the lessening in life expectancy imposed by air pollution. Ferronato and Torretta (2019) expressed their opinions regarding the significant impact of improper waste management and serious health problems due to contamination of the land, water, and air due to pollutant discharge, which are the vehicle for ailment transmission when improperly disposed of, treated, and managed. Wu et al. (2020) observed the chance that long-term experience to air pollution will augment COVID-19-related health problems and mortality.

Pye and Nenes (2020) proposed the atmospheric bitterness of particles and vapours and its effects on the health of people. According to Wu et al. (2020), as air is the most fundamental medium for transmission, it is important for these respiratory viruses to spread through various channels. The exposed droplets and aerosols also have an effect on human-to-human transmission by inducing death and speeding up infection rates (Shiu et al. 2019).

The risk of health deterioration is considerable as a result of both direct and indirect exposure to contaminated air (Weichenthal et al. 2014). Stark et al. (2010) concluded that there is a correlation between pollutant air and disorders in the heart and lungs. Augmented contact to air pollution, regardless of the source, has reduced health hazards. A raise in PM2.5 exposure causes inflammatory bowel disorders, connective tissue diseases, and an increased risk of rheumatoid arthritis (Adami et al. 2022). Exposure to air pollution raises chronic risks like asthma or lung cancer and psychiatric conditions like schizophrenia and depression (Newbury et al. 2021). Long-term exposure to fine particles alters the bloodstream's functioning, affecting how well the heart works. Additionally, coronary arteriosclerosis has been associated with compounds generated due to traffic emissions (Hoffmann et al. 2007).

3 Materials and methods

3.1 Data collection

We collected data on the daily air pollution and metrological and respiratory infection cases (https://cpcb.nic.in; https://main.mohfw.gov.in/documents/Statistics; https://www.covid19india.org/). This study used the fine particulate matter concentration from August 31, 2018, to August 31, 2021 (https://cpcb.nic.in) and considered 8760 h. We divide the collected records into two parts: the first is the training set (70%), and the second is the test set (30%). This study used the number of respiratory infections, influenzas, Pneumonia, and SARS-CoV-2 cases as the prediction target. The count of these cases was extracted from the public domain (https://main.mohfw.gov.in/documents/Statistics), managed by the Indian Government Health Cooperation. We considered the number of cases in India from January 1, 2020, to December 31, 2021.

3.2 Methods

First, to build the prediction performance, examine the association between the independent and the dependent variables. To build the forecast model for the respiratory infection cases, enhanced the regularisation with ANN first analyses the association between the dependent and the independent features**.** This model constructed the ANN model and evaluated the association between environmental features and respiratory infection cases**.** The approach used in the study is shown in Fig. 1.

3.3 Pre-processed data

There are some missing values, which were filled using the average of all the values for the particular feature.

3.4 Enhanced regularization

ANN model used in this study consists of 3 layers: input layers used for data input, multiple hidden layers, and an output layer that produces the final result—links the nodes of the hidden layer to the output layer step by step. Every connection has a value, and the updated value assists in the gradient descent process used to back propagate the weights between each layer, measuring the inaccuracy in the final output layer and optimising the weight. The enhanced

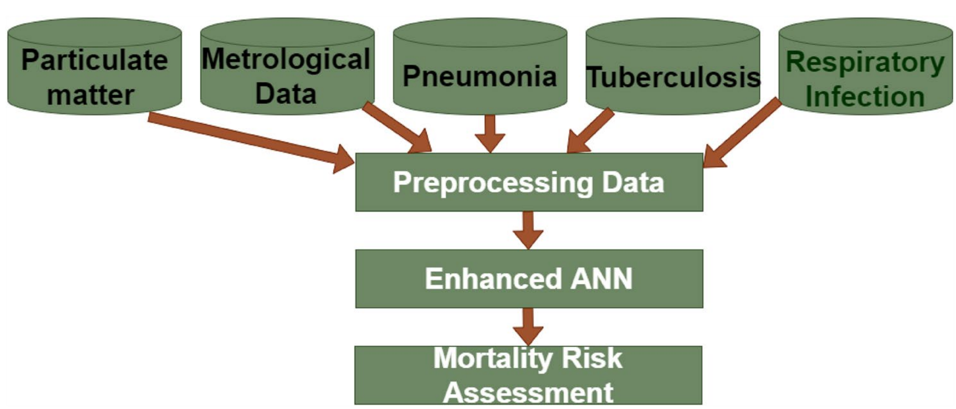

Fig. 1 Flow of the respiratory disease mortality assessment from Air Pollution

Regularization reduces the risk of overfitting the dataset by decreasing the overall size of the weights in the ANN model. The proposed Regularization in the loss function enhances the performance of the existing solution by removing the unwanted neurons and maintaining only the essential neurons, minimises the training set's overfitting and speeds up processing.

The weights will continue to grow over time in every iteration without this Regularization, which decreases the learning rate of the ANN model. It affects the prediction and makes the neural network more complex.

Regularization widens the applicability of the model and enhances its performance by maximizing the regularization coefficient's value to provide a model that fits the data well. Regularization determines how important this function is by adding the improved regularization term to the loss function. The general form is represented as

$$\text{Result} = \text{loss (truth, prediction)} + \text{regularization term}$$

$$\text{Improved Regularization Function (IRF)} = \sqrt[n]{a}.a^3$$

Regularization is a technique that calibrates the neural network in order to minimize the loss function and prevent overfit or underfit. It improves performance by learning the model parameters on new or unseen data. Even considering the huge dataset, the data available is minimal compared to the quantity of data the model accepts. Due to the lack of new data, the model may overfit and become adept at accurately representing the training data (Yao et al. 2020). However, it could perform better on new data, i.e., test data. This issue arises when the model has exhaustively trained on the training data that is available that it is unable to generalize successfully for fresh data.

Regularisation expands the model's applicability and enhances its performance by maximising the value to produce a well-fitted model. Regularisation enables deep learning algorithms to perform effectively with different inputs and is specifically intended to reduce error for both training and test data. The neural network's loss function determines how far the forecast values differ from the observed values. Adding the regularization term to the loss function determines how strongly the model will influence the training. The regularisation removes the unwanted neurons and works with the essential neurons. The processing time is reduced by disabling and discarding the undesirable neurons.

4 Experimental results

We collected the daily atmosphere data used in this study from the Indian government metrological websites (https://cpcb.nic.in). India has 270 stations for measuring air pollution, and each station's status is listed by the state. These stations continuously and automatically collect hourly data on air quality, and the information is available to everyone. Major air pollutants, i.e., PM2.5, PM10, CO, NO2, SO2, and O3, were collected from hourly measurements at the 270 monitoring stations in India from 1 January 2019 to 31 December 2021 (https://main.mohfw.gov.in/documents/Statistics). We collected the metrological data from the Indian government websites (https://main.mohfw.gov.in/documents/Statistics). The dataset contained pre-processed hourly values of temperature, humidity, wind speed, wind direction, and rainfall. Table 1 tabulates the statistics of the daily pollutant data, and Table 2 shows the statistics of the daily temperature data.

The first row in the table specifies the total number of samples in the specific feature. The remaining rows specify the statistics like the specific feature's mean, standard deviation, maximum, and minimum. Tables 1 and 2 used the same statistical measures.

Figure 2 shows the estimation of asthma due to air pollution in Andhra Pradesh. The total population in Amaravathi is 84,835, and the people affected by asthma are 7353 children, 225 youth, 895 adults, and 6674 elders. The total population in Rajamahendravaram is 561,000, and the people affected by asthma are 4526 children, 262 youth, 674 adults, and 2463 elders. The total population in Tirupati is 729,000, and the people affected by asthma are 73,452 children, 5732 youth, 8456 adults, and 53,631 elders. The total population in Visakhapatnam is 2,138,000, and the people affected by asthma are 35,633 children, 7355 youth, 3365 adults, and 7944 elders.

Figure 3 shows the estimation of Pneumonia due to air pollution in Andhra Pradesh. The total population in Amaravathi is 84,835, and the people affected by Pneumonia are 5456 children, 43 youth, 3254 adults, and 5467 elders. The total population in Rajamahendravaram is 561,000, and the people affected by Pneumonia are 23,631 children, 537 youth, 17,456 adults, and 26,832 elders. The total population in Tirupati is 729,000, and the people affected by Pneumonia are 164,578 children, 1385 youth, 74,743 adults, and

Table 1 Statistics of the daily pollutant data

	PM2.5	PM10	AQI
count	24,933.000000	18,391.000000	24,850.000000
mean	67.450578	118.127103	168.463581
std	64.661449	90.605110	140.696535
min	0.040000	0.010000	13.000000
25%	28.820000	56.255000	81.000000
50%	48.570000	95.630000	118.000000
75%	80.590000	149.745000	208.000000
max	949.990000	1000.000000	2049.000000

Table 2 Statistics of the daily temperature data

	YEAR	ANNUAL	JAN-FEB	MAR-MAY	JUN-SEP	OCT-DEC
count	117.000000	117.000000	117.000000	117.000000	117.000000	117.000000
mean	1959.000000	29.181368	24.629573	31.517607	31.193205	27.208120
sfd	33.919021	0.555555	0.911239	0.740585	0.420508	0.672003
min	1901.000000	28.110000	22.250000	29.920000	30.240000	25.740000
25%	1930.000000	28.760000	24.110000	31.040000	30.920000	26.700000
50%	1959.000000	29.090000	24.530000	31.470000	31.190000	27.210000
75%	1988.000000	29.470000	25.150000	31.890000	31.400000	27.610000
max	2017.000000	31.630000	28.330000	34.570000	32.410000	30.030000

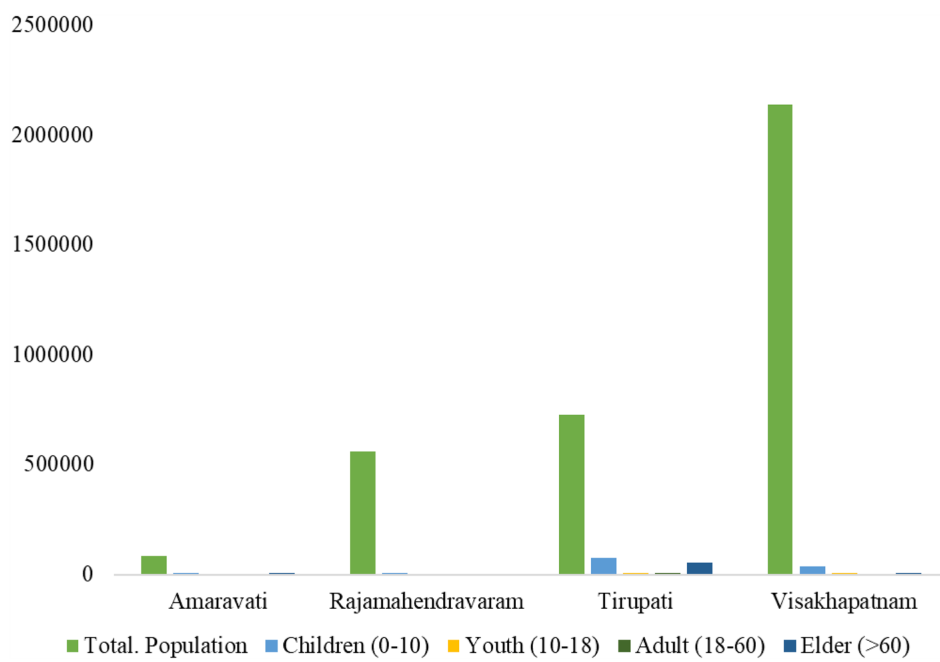

Fig. 2 Estimation of asthma in Andhra Pradesh due to the excess air pollution

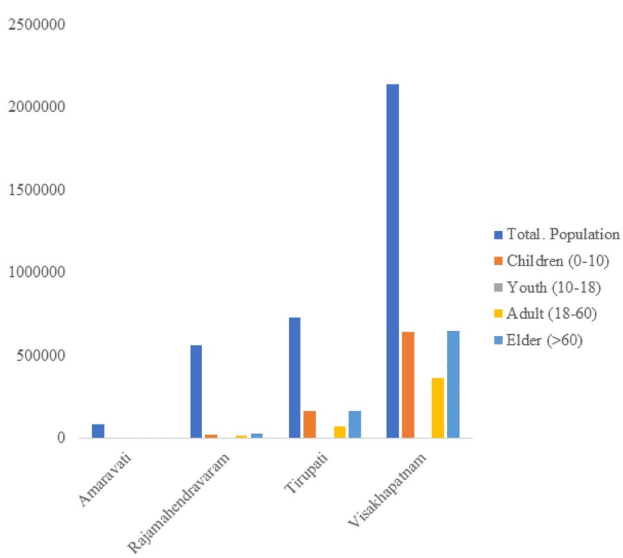

Fig. 3 Estimation of the Pneumonia in Andhra Pradesh due to excess air pollution

168,486 elders. The total population in Visakhapatnam is 2,138,000, and the people affected by Pneumonia are 646,671 children, 3545 Youth, 363,456 adults, and 649,574 elders.

4.1 Mortality risk assessment

Evaluated the proposed model and compared the predictive performance with other algorithms. Table 3 tabulates the performance and measurements of the LSTM, RNN, DNN, and LSTMGRU that have high predictive performance. The mean absolute error for assessing the asthma, Influenza, respiratory infection occurrence is approximately 6.55, and RMSE of about 6.19.

To predict the high or low risk of the spread of respiratory diseases due to air pollution, we used the improved ANN model, which divides the region into five categories: high-high, low-low, low–high, high-low, and no significant. High-high recognizes the areas with a high incidence of

Table 3 Results of different classifiers on the test data

Technique	Metric	Influenza	Pneumonia	Respiratory infection
Multiplelinear regression	RMSE	6.35	6.38	6.55
	MAE	6.71	6.74	6.72
	r	0.92	0.93	0.91
Artificial neural network	RMSE	11.86	11.83	11.85
	MAE	11.83	11.87	11.81
	r	0.71	0.69	0.64
Convolution neural network	RMSE	6.41	6.45	6.43
	MAE	6.44	6.45	6.46
	r	0.92	0.91	0.88
LSTM	RMSE	12.29	12.14	12.15
	MAE	12.18	12.20	12.13
	r	0.79	0.74	0.73
RNN	RMSE	10.12	10.13	10.13
	MAE	10.11	10.11	10.11
	r	0.61	0.63	0.64
LSTMGRU	RMSE	9.23	9.14	9.12
	MAE	9.15	9.18	9.11
	r	0.63	0.61	0.62
LSTMRNN	RMSE	7.31	7.42	7.36
	MAE	7.36	7.33	7.31
	r	0.51	0.53	0.56
DNN	RMSE	8.78	8.74	8.77
	MAE	8.72	8.73	8.72
	r	0.53	0.55	0.51
Proposed	RMSE	6.19	6.17	6.19
	MAE	6.55	6.52	6.56
	r	0.98	0.99	0.99

disease, and low-low recognizes those with a low incidence of disease. Table 4 tabulates the cumulative mortality rate and its processing time for affected states in India.

Figure 4 shows the estimation of the mortality risk using the various deep-learning models. The performance metrics MAE, RMSE, and r compare the existing deep learning models. The MAE for the proposed registered cases is 1.10, and for mortality, the risk is 1.45. The RMSE for the proposed registered cases is 4.57, and for mortality, the risk is 5.84. The r value for the proposed registered cases is 0.98, and for mortality risk is 0.99.

Table 5 tabulates the comparison of the performance metrics for respiratory infections using an enhanced ANN model. The highest accuracy for asthma is 99.95% in the state of Jharkhand. The lowest accuracy is 98.04% in the state of Rajasthan, the highest sensitivity for asthma is 99.85% in the state of Haryana, and the lowest sensitivity is 93.78% in the state of Rajasthan. The highest specificity for asthma is 99.75% in the state of Chhattisgarh. The lowest accuracy is 92.65% in the state of Rajasthan. The highest accuracy for Pneumonia is 99.86% in Arunachal Pradesh. The lowest accuracy is 93.84% in the state of Dadra and Nagar Haveli, the highest sensitivity for Pneumonia is 99.94% in the state of Nagaland, and the lowest sensitivity is 91.17% in the state of Gujarat, and the highest specificity for Pneumonia is 99.37% in state Haryana. The lowest accuracy is 91.46% in the state of Daman and Diu.

5 Discussion

The soluble air contaminants are harmful to human health. The drive of the air particles from the high concentration space to the low concentration space will increase the level of the pollutants. The finer-grained particles are going to stay around in the atmosphere for a longer period of time than the coarser-grained ones. Poor air quality damages the immune system and respiratory system and exacerbates the virus replication (Schraufnagel, et al. 2019), which leads to the risk of hospitalization and death (Urrutia-pereira et al. 2020).

Almost 4.2 million mortalities occurred due to air pollution as it damages the organs in the body especially respiratory and cardiovascular systems (Forouzanfar et al. 2015). Qin et al. (Qin et al. 2020) recognized the association between high mortality and air pollution and demonstrated that long-term exposure to harmful pollutants made people more susceptible to COVID-19. Asthma, cardiorespiratory disorders, and respiratory inflammation are all caused by prolonged exposure to air pollution. One of the main environmental health risk factors responsible for many million fatalities annually worldwide is fine particle matter (Lelieveld et al. 2015).

Particulate matter adversely affects respiratory diseases (Forouzanfar et al. 2015), and long-term exposure to this pollutant worsens asthma symptoms (Qin et al. 2020).

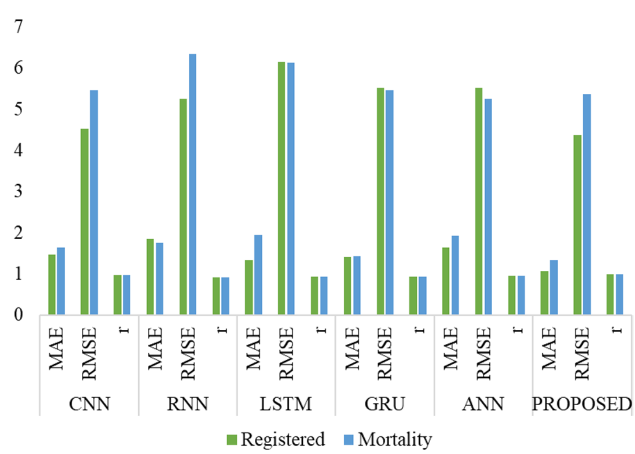

Fig. 4 Comparison of the mortality risk of the proposed with the existing models

Table 4 Cumulative mortality rate for affected states in India

State	Pneumonia			Asthma		
	Actual	Predicted	PT	Actual	Predicted	PT
Andaman and Nicobar Island	23	20	6.13	7	7	6.12
Andhra Pradesh	365	368	9.99	587	585	9.99
Arunachal Pradesh	0	3	8.02	0	0	6.25
Assam	135	134	4.87	261	266	7.67
Bihar	25	26	6.41	2	5	7.18
Chandigarh	215	215	5.57	15	16	5.58
Chhattisgarh	47	45	7.91	35	36	7.98
Dadra and Nagar Haveli	23	23	5.72	8	9	5.72
Daman and Diu	2	2	4.57	0	2	4.57
Goa	74	76	7.42	53	51	7.42
Gujarat	3	3	8.44	3	3	7.44
Haryana	34	37	8.71	38	34	7.71
Himachal Pradesh	107	107	9.34	145	143	7.38
Jammu and Kashmir	9	11	9.88	0	0	2.88
Jharkhand	4	4	9.24	0	0	1.25
Karnataka	142	146	8.32	10	10	5.32
Kerala	44	48	8.97	109	109	8.99
Lakshadweep	0	5	6.48	0	0	5.48
Madhya Pradesh	104	105	9.16	35	34	7.99
Maharashtra	27	25	5.11	87	87	5.11
Manipur	0	0	5.66	10	18	5.66
Meghalaya	39	35	6.47	28	28	6.48
Mizoram	32	38	5.89	6	6	5.87
Nagaland	1	4	9.91	45	44	9.91
NCT of Delhi	723	723	7.82	492	495	7.82
Odisha	279	279	9.87	6	6	8.89
Puducherry	74	74	6.63	33	33	6.66
Punjab	22	26	9.37	58	57	8.39
Rajasthan	98	97	8.25	24	24	5.425
Sikkim	0	0	8.69	25	24	4.69
Tamil Nādu	757	757	7.13	18	18	5.13
Telangana	2	5	8.82	65	65	7.87
Tripura	17	17	7.27	0	0	3.27
Uttar Pradesh	126	126	7.56	86	86	7.59
Uttarakhand	0	4	6.23	699	699	5.23
West Bengal	660	660	5.52	732	734	5.51

*Processing time-PT

During the flu season, there was a correlation between the particulate matter (PM2.5) and influenzas in Beijing, China (Feng et al. 2016). If the viruses adhere to the particulate matter, they stay airborne for a long period and can spread through the air (Lindsley et al. 2010). The negative effect of the particulate matter enhances the viral replication in the human respiratory system (Xian et al. 2020).

Exposure to increasing levels of air pollution lowers life expectancy and affects the respiratory and cardiovascular systems (Casee and Newby 2011). Small particles have the highest deposition in the lungs and extrapulmonary resulting in systemic inflammation (Tseng et al. 2017). Particulate matter functions as a carrier for many viruses and increases the spread of the virus in the aerosol because it creates a microenvironment suitable for the virus persistence (Setti et al. 2020). Pollution is primarily caused by the harmful effect, and specific particle components provide sustenance for bacteria that serve as carriers (Wei et al. 2020). Cui et al. (Cui et al. 2003) proved that the regions with high air pollution index have double the chance of death than the regions with low air pollution index and concluded that prolonged exposure to the particulate matter might increase

Table 5 Comparison of the performance metrics for respiratory infections using Enhanced ANN model

State	Asthma			Pneumonia		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
Andaman and Nicobar Island	99.24	99.76	99.67	96.56	94.67	93.45
Andhra Pradesh	99.17	97.26	97.48	95.75	97.24	95.35
Arunachal Pradesh	99.07	99.84	99.63	99.86	93.35	95.74
Assam	99.89	98.83	98.37	98.36	98.26	93.25
Bihar	99.06	97.26	99.38	99.36	97.25	93.26
Chandigarh	99.66	99.37	99.37	96.75	94.26	95.32
Chhattisgarh	99.84	99.47	99.75	99.47	92.35	95.25
Dadra and Nagar Haveli	99.26	96.84	97.47	93.84	91.62	95.62
Daman and Diu	99.82	99.37	99.58	97.26	93.63	91.46
Goa	99.15	98.84	98.47	95.64	94.37	98.26
Gujarat	99.92	95.84	96.85	95.84	91.17	96.28
Haryana	99.91	99.85	99.47	99.26	92.73	99.37
Himachal Pradesh	98.42	98.85	97.94	98.15	92.42	97.27
Jammu and Kashmir	99.17	94.87	95.27	99.36	95.22	94.84
Jharkhand	99.95	99.84	99.45	95.25	92.15	93.64
Karnataka	99.46	99.37	99.25	97.25	96.13	95.63
Kerala	99.35	98.95	98.16	95.74	95.41	93.74
Lakshadweep	99.26	99.85	98.93	99.46	93.23	98.74
Madhya Pradesh	99.26	99.26	96.86	94.25	93.14	96.73
Maharashtra	99.28	99.96	97.84	98.85	96.24	93.63
Manipur	99.47	99.37	94.78	98.85	94.14	94.63
Meghalaya	99.36	99.84	95.75	96.84	92.18	95.46
Mizoram	99.37	96.95	94.85	99.26	94.19	95.74
Nagaland	99.57	99.68	97.48	97.36	99.94	97.74
NCT of Delhi	99.36	99.37	95.85	96.84	99.53	95.74
Odisha	99.85	95.84	94.84	95.15	94.25	93.26
Puducherry	99.84	99.84	95.86	96.25	94.63	95.26
Punjab	98.89	98.84	98.53	98.25	92.85	93.28
Rajasthan	98.04	93.78	92.65	94.26	94.25	92.57
Sikkim	98.36	99.85	94.75	98.52	99.36	94.83
Tamil Nādu	99.47	95.85	97.37	95.25	93.34	97.74
Telangana	99.84	98.85	95.63	96.15	94.32	95.44
Tripura	99.59	99.47	94.63	97.94	92.34	94.65
Uttar Pradesh	99.26	94.74	96.83	94.64	94.25	96.46
Uttarakhand	99.63	97.57	95.84	95.73	94.46	95.75
West Bengal	99.42	99.58	94.63	97.83	92.26	94.63

the mortality rate. Prolonged exposure to high quantities of particulate matter threats to older adults compromises the lung and the cardiovascular tissue (Sancini et al. 2014).

The major drawback of the traditional models like Markov chain models, linear regression, and the autoregressive integrated moving average is the creation of bias in the estimation of the air pollution-related health impacts like asthma, tuberculosis, and respiratory infections. To overcome the limitations of the linear mapping and prioritize the dataset before predicting the future outbreak. We proposed the improved ANN to prevent bias in predicting the infection outbreak due to air pollution. To represent the relationship between the environmental factors with infectious respiratory cases, we generated the prediction model using the enhanced ANN. The results proved that the highest R2 value of 0.35 outperformed the existing models.

From the results, we observed that the proposed minimized the computational error. To overcome the drawbacks of conventional models, the enhanced ANN was proposed to minimize the error in predicting respiratory casualty because of air pollution. We generated the prediction model using the enhanced ANN to represent the relationship between environmental factors and infectious respiratory cases. Among the limitations of this study are the following: we did not include individual-level data, especially demographic data.

6 Conclusion

The virus-laden particles that are < 5 um in diameter is related to respiratory infections in individuals, and this virus would remain in the air for hours. For sustainable life, air quality is very crucial for human beings. This study proposes a risk assessment model for respiratory diseases using the improved regularization in the artificial neural network. Finally, we conclude that particulate matter and temperature could promote the transmission of asthma, Pneumonia, Influenza, and SARS-CoV-2. The main benefit of the proposed method is the early notification system based on the environment for chronic patients and alarming to all illness categories. It could be widely used by suitably altering the model's parameters to be acceptable for particular nations in order to collect the data. The future work will be tested on the cardiorespiratory datasets and will try to improve its computational methods. There are several limitations to this study. First, we did not include the individual-level data, especially demographic data. Second, we cannot assess the rate of hospitalization due to some other comorbidities.

6.1 Future work

In the future, the work will be tested on cardiorespiratory datasets, and its computational methods will be improved.

Funding Not applicable.

Data availability N/A.

Declarations

Conflict of interest All authors do not have any conflict of Interest.

References

Adami G, Pontalti M, Cattani G, Rossini M, Viapiana O, Orsolini G, Fassio A (2022) Association between long-term exposure to air pollution and immune-mediated diseases: a population-based cohort study. RMD Open 8(1):e002055

Antonio C, Jane E, Emil K, Rory JS (1996) Thunderstorm associated asthma: a detailed analysis of environmental factors. J Med 312:604–607

Bert B, Stephen TH (2002) Air pollution and Health. Lancet 360:1233–1242

Burnett R, Chen H, Szyszkowicz M, Fann N, Hubbell B, Pope CA III, Spadaro JV (2018) Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. Proc Natl Acad Sci 115(38):9592–9597

Casee FRM, Newby DE (2011) Cardiovascular effects of inhaled ultrafine and Nano sized particles. Wiley and Sons, UK

Chakraborty T, Jamal RF, Battineni G, Teja KV, Marto CM, Spagnuolo G (2021) A review of prolonged Post-COVID-19 symptoms and their implications on dental management. Int J Environ Res Public Health 18(10):1–14

Conticini E, Frediani B, Caro D (2020) Can atmospheric pollution be considered a cofactor in extremely high levels of SARS-CoV-2 lethality in Northern Itlay? Environ Pollut 261:1–3

Cui Y, Zhang ZF, Froines J, Zhao J, Wang H, Yu SZ, Detels R (2003) Air pollution and case fatality of SARS in the peoples republic of China: an ecological study. Environ Health 2(1):15

Exarchos KP, Belstiou M, Votti CA, Kostikas K (2020) Artificial Intelligence techniques in asthma: a systematic review and critical appraisal of the existing literature. J Eur Respir 56(3):1–11

Feng C, Li J, Su W, Zhang Y, Wang Q (2016) Impact of ambient fine particulate matter (PM2.5) exposure on the risk of influenza like illness: a time series analysis in Beijing China. Environ Health 15:17–25

Ferronato N, Torretta V (2019) Waste mismanagement in developing countries: a review of global issues. Int J Environ Res Public Health 16(6):1060

Forouzanfar MH, Afshin A, Alexander LT, Anderson HB, Brutta ZA, Birykov S et al (2015) Global regional and national comparative risk assessment of 79 behavioural environmental and occupational and metabolic risks or clusters of risks 1990–2015: a systematic analysis for the global burden of disease study. Lancet 388:1659–1724

Gorai A, Tchounwou P, Tuluri F (2016) Association between ambient air pollution and asthma prevalence in different population groups residing in eastern Texas, USA. Int J Environ Res Public Health 13(4):1–17

Hao Y, Linyu X (2018) Comparative study of PM10/Pm2.5-bounds PAHs in downtown Beijing, Chine: concentrations, sources and health risks. J Clean Product 177:674–683

Hoffmann B, Moebus S, Mohlenkamp S, Stang A, Lehmann N, Dragano N, Jockel KH (2007) Residential exposure to traffic is associated with coronary atherosclerosis. Circulation 116(5):489–496

https://cpcb.nic.in

https://main.mohfw.gov.in/documents/Statistics

https://www.covid19india.org/

Hunter JS (1986) The exponentially weighted moving average. J Qualit Technol 18:203–210

Iha Y, Kinjo T, Parrott G, Higa F, Mori H, Fujita J (2016) Comparative epidemiology of influenza A and B viral infection in a subtropical region: a 7-year surveillance in Okinawa, Japan. BMC Infect Dis 16(1):650–657

Jennifer KM, John RB, Tim AB, Kathleen MM, Helene GM, Boriana P, Katharine H, Fredrick WL, Ira BT (2010) Short term effects of air pollution on wheeze in asthmatic children in Fresno. Cal Environ Health Perspect 118(1497):1502

Killerby M, Biggs H, Haynes A, Dahl R, Mustaquim D, Gerber S et al (2018) Human coronavirus circulation in the united states 2014–2017. J Clin Virol 101:52–56

Ko FW, Tam W, Wong TW, Lai CK, Wong GW, Leung TF, Ng SS, Hui DS (2007) Effects of air pollution on asthma hospitalization rate in different age groups in Hong Kong. Clin Exposure Allergy 37:1312–1319

Lee HJ, Kim YW, Lee HS, Jang YJ (2016) A cluster analysis on the risk of particulate matter focusing on differences of risk related behaviors based on public segmentation. J Public Relations Res 20:201–235

Lelieveld J, Evans JS, Fnais M, Giannadaki D, Pozzer A (2015) The contribution of outdoor air pollution sources to premature mortality on a global scale. Nature 525:367–371

Lelieveld J, Klingmüller K, Pozzer A, Pöschl U, Fnais M, Daiber A, Münzel T (2019) Cardiovascular disease burden from ambient air pollution in Europe reassessed using novel hazard ratio functions. Eur Heart J 40(20):1590–1596

Lindsley W, Blachere F, Dabis K, Pearce T, Fisher M, Khakoo R et al (2010) Distribution of airborne influenza virus and respiratory syncytial virus in an urgent care medical clinic. Clin Infect Dis 50(5):639–648

Lipsitch M (2020) Seasonality of SARS-CoV-2: will covid-19 go away on its own in warmer weather

Luo C, Yao L, Zhang L, Yao M, Chen X, Wang Q et al (2020) Possible transmission of severe acute respiratory syndrome coronavirus2(SARS-CoV-2) in a public bath centre in Huai'an Jiangsu Province. China JAMA Network OPen 3(3):1–11

Newbury JB, Stewart R, Fisher HL, Beevers S, Dajnak D, Broadbent M, Bakolis I (2021) Association between air pollution exposure and mental health service use among individuals with first presentations of psychotic and mood disorders: retrospective cohort study. Br J Psychiatry 219(6):678–685

Pye HO, Nenes A, Alexander B, Ault AP, Barth MC, Clegg SL, Zuend A (2020) The acidity of atmospheric particles and clouds. Atmos Chem Phys 20(8):4809–4888

Qin C, Zhou L, Hu Z, Zhang S, Yang S, Tao Y, Xie C, Ma K, Shang K, Wang W, Tian SD (2020) Dys regulation of immune response in patients with COVID-19 in Wuhan China. Clin Infect Disease 71(15):762–768

Rajagopalan S, Al-Kindi SG, Brook RD (2018) Air pollution and cardiovascular disease: JACC state-of-the-art review. J Am Coll Cardiol 72(17):2054–2070

Renato A, Giorgio WC, Giovanni P (2010) Possible role of climate changes in variations in pollen seasons and allergic sensitizations during 27 years. Annals Allergy Asthma Immunol 104:215–222

Robert AS, Kazuhiko I (2010) Age related association of fine particles and ozone with severe acute asthma in new York city. J Allergy Clin Immunol 125:367–373

Sancini G, Farina F, Battaglia C, Cifola I, Mangano E, Mantecca P, Camatini M, Palestini P (2014) Health risk assessment for air pollutants: alterations in lung and cardiac gene expression in mice exposed to Milano winter fine particulate matter (PM2.5). PLoS ONE 9:e109685

Schraufnagel DE et al (2019) Air pollution and non communicable diseases: a review by the forum of international respiratory societies environmental committee, Part 2: Air pollution and organ systems. Chest 155:417–426

Setti L, Passarini F, De Gennaro G, Di Gilio A, Palmisani J, Buono P, Fornari G, Perrone MG, Piazzalunga A, Barbieri P, Rizzo E, Miani A (2020) Evaluation of the potential relationship between particulate matter pollution and COVID-19 infection spread in Italy. Soc Ital Di Med Ambientale 2:1–6

Shiu EY, Leung NH, Cowling BJ (2019) Controversy around airborne versus droplet transmission of respiratory viruses: implication for infection prevention. Curr Opin Infect Dis 32(4):372–379

Strak M, Boogaard H, Meliefste K, Oldenwening M, Zuurbier M, Brunekreef B, Hoek G (2010) Respiratory health effects of ultrafine and fine particle exposure in cyclists. Occup Environ Med 67(2):118–124

Sutyajeet S, Chengsheng J, Jared F, Crystal RU, Clifford M, Amir S (2016) Exposure to extreme heat and percipation events associated with increased risk of hospitalization for asthma in Maryland, USA. Environ Health 15:1–14

Tseng CY, Wang JS, Chao MW (2017) Causation by diesel exhaust particles of endothelial dysfunctions in cytotoxicity, pro-inflammation, permeability and apoptosis induces by ROS generation. Cardiovascular Toxicol 17:384–392

Urrutia-pereira M, Mello-da-silva CA, Sole D (2020) COVID-19 and air pollution: a dangerous association? Allergol, Immunopathol 48(5):496–499

Wei M, Liu H, Chen J, Xu C, Li J, Xu P, Sun Z (2020) Effects of aerosol pollution on PM25 assoicated bacteria in typical inland and coastal cities of northern China during the winter heating season. Environ Pollut 262:114188

Weichenthal S, Hatzopoulou M, Goldberg MS (2014) Exposure to traffic-related air pollution during physical activity and acute changes in blood pressure, autonomic and micro-vascular function in women: a cross-over study. Part Fibre Toxicol 11(1):1–16

Wu X, Nethery RC, Sabath MB, Braun D, Dominici F (2020) Air pollution and COVID-19 mortality in the United States: strengths and limitations of an ecological regression analysis. Sci Adv 6(45):eabd4049

Xian M, Ma S, Wang K, Lou H, Wang Y, Zhag L et al (2020) Particulate matter 2.5 causes deficiency in barrier integrity in human nasal epithelial cells. Allergy Asthma Immunol Respir 12(2):56–71

Yang J, Zhang M, Chen Y, Ma L, Yadikaer R, Lu Y, Lou P, Pu Y, Xiang R, Rui B (2020) A study on the relationship between air pollution and pulmonary tuberculosis based on the general additive model in Wulumuqi, China. Int J Infect Dis 96:42–47

Yao Y, Pan J, Liu Z, Meng X, Wang W, Kan H, Wang W (2020) Temporal association between particulate matter pollution and case fatality rate of COVID-19 in Wuhan, China. Environ Res 189:1–3