Using deep learning to identify asthmatic children who are sensitive to PM exposure: the road to personalized risk prediction and intervention

Dohyeong Kim
University of Texas at Dallas

Abstract

The study aims to develop a personalized intervention strategy for self-management behavior by predicting PM-related asthma exacerbation via deep learning (DL) and evaluate its effectiveness. Between 2020-2023, 181 pediatric asthma patients were recruited from nine hospitals in South Korea. Real-time PM data from personal devices and daily asthma symptom records were used to develop a 1D Convolutional Neural Network-Long Short-Term Memory model forecasting asthma exacerbation based on 3-day $PM_{2.5}$ observations. Additional 109 patients recruited were classified into three groups based on self-assessment and prediction results. The personalized group received alarm messages based on predicted personal risks, while the standard group received messages by PM forecast for the next day. An individualized self-management behavior intervention alert system by DL-based risk prediction could have potential to reduce asthma exacerbation triggered by personal PM exposure. These findings emphasize the importance of personalized intervention in asthma management to achieve better outcomes for pediatric asthma.

I. Introduction

Exposure to particulate matter (PM) has been recognized as a prominent trigger for exacerbating pediatric asthma, leading to heightened asthmatic symptoms.[1-3] This exacerbation results in increased hospital visits and impaired lung function, particularly affecting affected individuals.[2] However, asthma's multifaceted nature, shaped by genetic and environmental factors, yields diverse phenotypes and endotypes.[4-7] Consequently, not all pediatric asthma patients display sensitivity to PM. Beyond endotype-related distinctions, this sensitivity hinges on disease severity, medication adherence, asthma control, and individual lifestyle choices.

Many studies on the correlation between PM exposure and asthma exacerbation have predominantly relied on stationary monitoring,[8-13] overlooking individual-level real-time monitoring encompassing living environments and behavioral patterns. Given PM monitoring's significant fluctuations influenced by factors like aerosol size and meteorological conditions,[14] it is imperative to integrate continuous, real-time monitoring of personal indoor and outdoor PM exposure. While some recent studies have attempted to gauge individual PM exposure using personal monitoring devices,[15, 16] none have applied interventions based on such device-derived data. Traditional air quality alarm interventions have shown promise in reducing exposure to ambient air pollutants,[13, 17] yet their effectiveness

varies among vulnerable groups due to uniform interventions driven by station-based monitoring data. Considering the individual variability in susceptibility to PM exposure, personalized self-management behavior interventions can be more pragmatic than uniform approaches.

Recent asthma research has harnessed machine learning (ML) and deep learning (DL) methods to predict asthma risks.[18-21] Their capacity to handle extensive data and unveil intricate patterns unapparent through traditional statistical methods[22] makes ML-based approaches adept at generating personalized risk predictions.[23, 24] Particularly, considering their prowess in handling intricate air quality data,[25] AI-based techniques prove well-suited for personalizing predictions of asthma exacerbation due to PM exposure. However, the pursuit of evaluating AI-powered personalize prediction and behavior intervention is still in the early stage and requires further development.

Addressing this gap, we gathered real-time individual PM exposure data through portable monitoring devices, concurrently tracking daily symptoms. By tailoring portable PM monitors for individual users, we systematically amassed genuine exposure and symptom pattern data. We subsequently harnessed a robust big data architecture to forecast the individualized likelihood of asthma exacerbation triggered by PM exposure. We employed a DL model to identify pediatric asthma patients sensitive to PM exposure, leveraging real-time indoor and outdoor PM data collected through individual portable devices and a mobile app. Moreover, we pioneered a personalized mobile alarm intervention, offering self-management behavior intervention based on the DL model's asthma exacerbation predictions and assessed its effectiveness compared to standard intervention group. This research underscores the potential of AI-based classification in identifying pediatric asthma patients sensitive to PM exposure. Additionally, it provides evidence for developing personalized medication to mitigate asthma exacerbation due to PM exposure.

II. Method

Over a span of three years between 2020 and 2023, we conducted the recruitment of pediatric asthma patients from 9 hospitals in South Korea (Table 1). The recruitment and data collection took place during the period of October-March, coinciding with South Korea's season with highest particulate matter concentration. In the initial and subsequent years, we enrolled 89 patients (October 2020 – March 2021) and 107 patients (October 2021 – March 2022), respectively, to establish the DL model. Since 33 patients from the first year were also included in the

second year's cohort, a cumulative total of 181 patients participated in constructing the DL model. During the third year (October 2022 – March 2023), 109 patients were assessed whether they would be sensitive to PM exposure through the model. Following a month of the model learning from their data, these patients were categorized into two groups: standard intervention and personalized intervention. Subsequently, these patients received asthma exacerbation prediction alarms with self-management behavior message for one month[i].

Table 1. Number of patients by period

Recruitment purpose	Period	# of patients	Total # of patients for modeling
Data collection and model construction phase	1st year: 2020/10 – 2021/03	89	163
	2nd year: 2021/10 – 2022/03	107	
Intervention phase	3rd year: 2022/10 – 2023/03	109	109

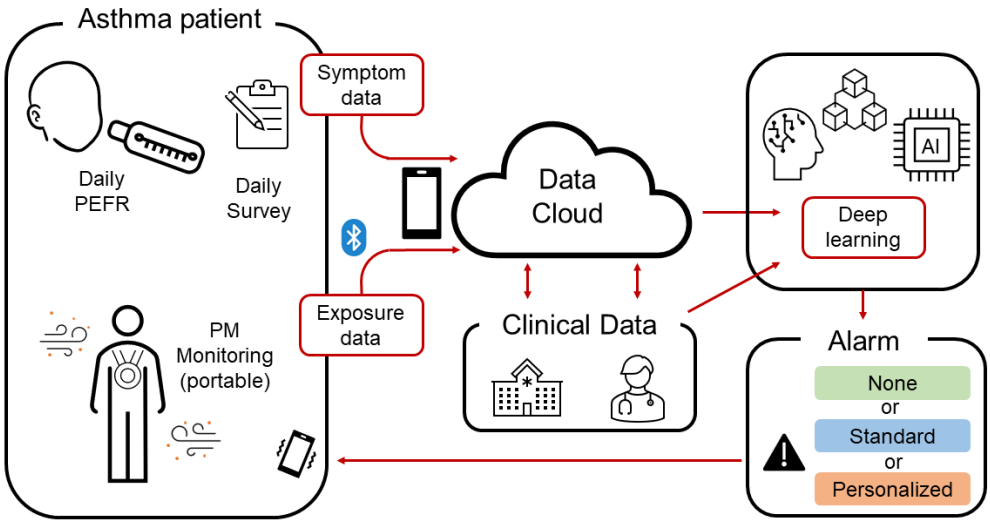

Figure 2. Personalized asthma exacerbation prediction and intervention framework

[i] Before enrolling in the study, all caregivers were given detailed explanations about the study's objectives and procedures, and their consent for participation was obtained.

In recent years, the growing computing power and availability of big data have led to the increasing popularity of DL based methods, which offer advantages over conventional ML or rule-based approaches.[26, 27] DL is a subset of machine learning that utilizes neural networks to automatically learn hierarchical data structure. While ML remains effective when data is limited and has linear structure, DL algorithms hold promise due to their ability to execute multiple nonlinear transformations, extracting higher-level abstractions from air quality data.[25]

In this study, we utilized the 1-dimensional Convolutional Neural Network Long Short-Term Memory (1D CNN-LSTM), a widely adopted approach for analyzing time-series air quality data, particularly PM.[28, 29] The CNN-LSTM is a fusion of LSTM's time-series capabilities with CNN's feature extraction strengths.[28] Specifically, the primary advantage of the CNN-LSTM model lies in its effective capture of both the inter-dependency and intra-dependency of spatiotemporal data, a critical aspect often overlooked in many studies focusing on air quality data modeling.[30] By incorporating enhancements such as batch normalization and dropout layers, the CNN-LSTM model outperforms individual CNN or LSTM models in spatiotemporal prediction of PM concentrations.[28, 29]

Our 1D CNN-LSTM model, comprising three 1D CNN layers followed by one LSTM layer, is designed to predict asthma exacerbation based on 3-day PM2.5 observations (Figure 3). The CNN layers employ kernels of size 1x7, 1x5, and 1x3 with 256, 128, and 64 channels, respectively, and include batch normalization and Rectified Linear Unit (ReLU) activation function. The LSTM layer is composed of 64 hidden neurons[ii]. Unlike standalone CNN or LSTM architectures, our model begins with a CNN component to extract features from the data, which are then used by the LSTM for forecasting, enabling the estimation of PM concentrations and meteorological parameters. The 1D CNN effectively captures local patterns and feature representations in time-series data, while the LSTM, being a recurrent neural network, captures long-term dependencies, making it suitable for processing time-series data.

[ii] To optimize the model, we employed the Adam optimizer[31] with a learning rate of 1e-5 and a batch size of 5. To ensure robustness, we implemented 5-fold cross-validation. All input data was scaled within the quantile range to minimize the impact of outliers. Model performance was evaluated using the validation dataset, and the best-performing model was selected after 500 epochs.

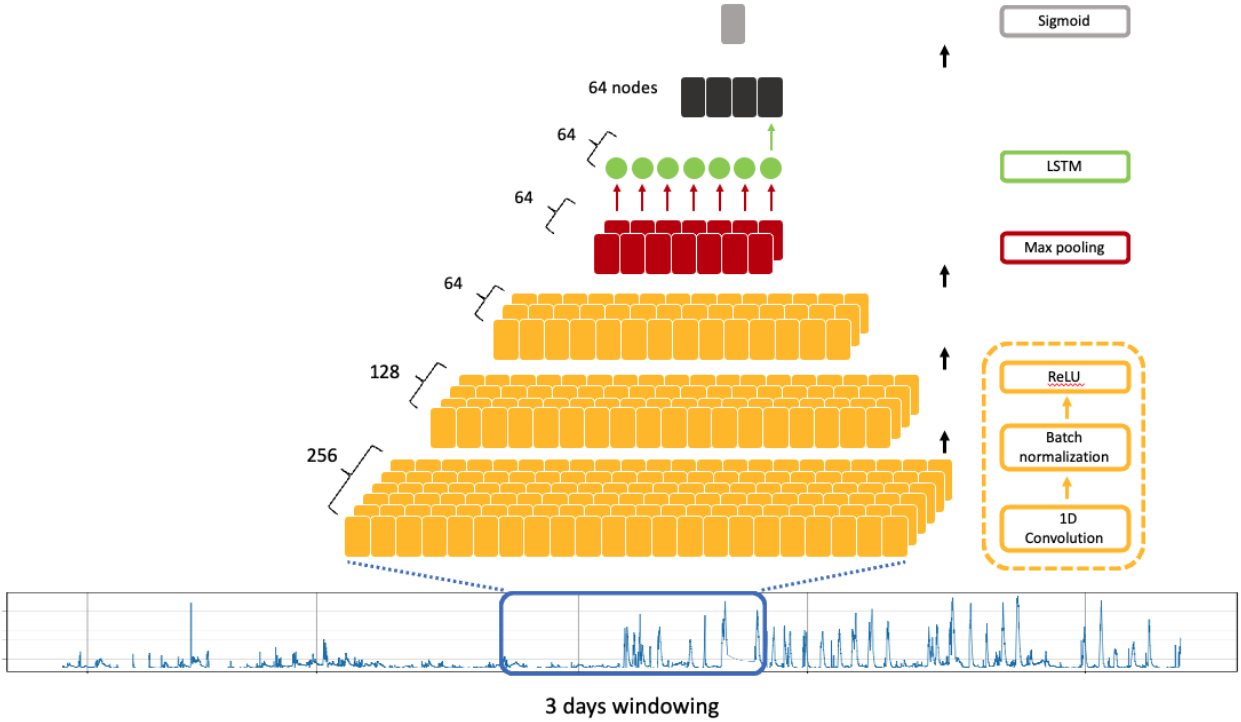

Figure 3. 1D CNN-LSTM model for timeseries data analysis

During the final phase of participant recruitment, individuals were initially categorized into a sensitive and a non-sensitive group based on their medical history, indicating whether their asthma symptoms worsened with PM exposure (Figure 4). After a one-month follow-up, if the prediction accuracy for each participant exceeded 80%, they were placed in the 'personalized intervention group'. These patients received personalized risk prediction with self-management behavior intervention when the DL model predicted asthma exacerbation from PM exposure.

On the other hand, if the classification accuracy for each participant was less than 80%, they were assigned to the 'standard intervention group', representing a population-based intervention. They received self-management behavior intervention when the Korea Meteorological Administration (KMA) forecasted “bad” PM conditions (when PM 2.5 levels are above 35 or PM 10 levels are above 80). Patients categorized as non-sensitive by both historical data and the DL model were included in the 'no intervention group', and they did not receive any interventions.

III. Results

Among the 109 patients, 28 were in the personalized intervention group, 46 in the standard intervention group, and 35 received no intervention. The proportion of males was similar across the groups, with 60% (19), 58.7% (27), and 67.9% (21) of patients in each intervention group, respectively. The average age also showed no significant differences among the groups, with a mean age of 10.46 ± 2.65 years (Table 2).

Statistically significant differences were found in asthma severity and asthma control at baseline (p-values of 0.032 and 0.008, respectively). The standard intervention group had a higher proportion of patients with moderate asthma severity (43.5%), while the other two groups had more patients with mild asthma severity (42.9% and 48.6%). Within the standard intervention group, more than half (54.3%) of the patients had uncontrolled asthma, whereas in the personalized group, the distribution was balanced, with an equal number of 9 patients experiencing uncontrolled and well-controlled asthma. The assessment of symptom control is based on the 2020 GINA guideline (Table 3).

Table 2. Patient characteristics

	Personalized intervention	Standard intervention	No intervention
No. of patients	28	46	35
Gender, male/female	19/9	27/19	21/14
Age	10.29±2.75	10.93±2.59	9.97±2.62
Height	141.56±16.32	144.62±15.31	139.23±18.20
Weight	41.92±17.76	44.30±15.63	39.85±17.50
PFT (%)			
FEV1	91.32 ±13.27	84.59 ±16.23	88.48 ±11.98
FVC	94.24 ±21.47	91.74 ±14.80	96.30 ±12.89
MMEF	82.43 ±19.83	75.83 ±24.97	76.39 ±20.36
Asthma severity			
Mild asthma	25	25	26
Moderate asthma	3	20	9
Severe asthma	0	1	0
ICS dose, none/low/medium	11/17/0	11/27/8	12/21/2
Allergic rhinitis, no/yes	6/22	9/37	7/28
Atopic dermatitis, no/yes	24/2	39/7	28/7
Food allergy, no/yes	24/4	42/4	31/4
Asthma symptom control			
Uncontrolled	9	25	7
Partly controlled	9	14	20
Well controlled	10	7	8
Mean PEFR diurnal variation	5.58 ±3.10	7.77 ±4.64	7.30±4.64

BMI	20.05 ±4.52	20.54 ±4.36	19.70 ±4.70
bronchiolitis obliterans, no/yes	26/0	45/1	35/0
Broncho-Pulmonary Dysplasia, no/yes	27/0	45/1	35/0

In the first and second phases, we utilized the 1D CNN-LSTM model to predict asthma exacerbation and obtained a mean classification performance through 5-fold cross-validation (Table 4). The results showed an accuracy of 86.1%, precision of 63.6%, sensitivity of 71.4%, specificity of 89.3%, and an area under the receiver operating characteristic (AUROC) of 0.872.

Table 3. 1D CNN-LSTM model performance

	Accuracy	Precision	Sensitivity	Specificity	AUROC
1st trial	0.852	0.632	0.614	0.911	0.833
2nd trial	0.858	0.626	0.707	0.895	0.883
3rd trial	0.849	0.589	0.789	0.863	0.886
4th trial	0.896	0.725	0.771	0.927	0.908
5th trial	0.851	0.611	0.690	0.891	0.851
Mean	0.861	0.636	0.714	0.893	0.872

Abbreviation: AUROC, Area under receiver operating characteristic.

IV. Discussion and Conclusion

We employed a DL model to predict asthma exacerbation with real-time indoor and outdoor PM data collected using individual portable devices and a mobile app. Additionally, we implemented a personalized self-management behavior intervention based on the DL model's asthma exacerbation predictions. Notably, while no significant changes were observed in the no-intervention and standard intervention groups, the personalized intervention group, guided by the DL model, exhibited substantial reductions. Between-group comparisons indicated

that the personalized intervention group had significantly lower odds of experiencing exacerbated asthma due to PM exposure.

These findings offer valuable insights into the efficacy of personalized interventions for managing asthma exacerbation triggered by PM exposure. The personalized intervention strategy, leveraging a DL model to predict asthma exacerbation, facilitates timely delivery of tailored alert messages, empowering patients to adopt appropriate self-management behaviors. By incorporating individual patient characteristics and real-time PM exposure data, this approach overcomes limitations of generalized interventions, demonstrating promising potential to enhance asthma management.

While the study's results are promising, several limitations deserve consideration. The present study focused on the effectiveness of personalized behavioral interventions within the real-life settings of pediatric asthma patients, emphasizing generalizability through multicenter recruitment. However, the study's representation is confined to South Korean pediatric asthma patients. Future research is warranted to extend conclusions to more diverse populations with varying ages, ethnicities, and including non-asthmatic patients. Additionally, the study's short duration and small sample size could limit generalizability, necessitating further research with a larger and more diverse cohort for comprehensive validation.

In conclusion, tailored personalized self-management behavior intervention informed by the DL model's predictions resulted in significant decreases in asthma exacerbation caused by PM exposure. These results underscore the significance of customized strategies in managing asthma for improved results. The integration of DL models into personalized interventions holds a promising avenue for the progression of personalized healthcare in the context of asthma.

Reference

1. Matsui EC, Abramson SL, Sandel MT, Dinakar C, Irani AM, Kim JS, Mahr TA, Pistiner M, Wang J, Lowry JA, Ahdoot S. Indoor environmental control practices and asthma management. Pediatrics. 2016 Nov 1;138(5), https://doi.org/10.1542/peds.2016-2589.

2. Kyung SY, Jeong SH. Particulate-matter related respiratory diseases. Tuberculosis and respiratory diseases. 2020 Apr;83(2):116, https://doi.org/10.4046/trd.2019.0025.

3. Kim SH, Yang HJ, Jang AS, Kim SH, Song WJ, Kim TB, Ye YM, Yoo Y, Yu J, Yoon JS, Jee HM. Effects of particulate matter in ambient air on the development and control of asthma. Allergy, Asthma & Respiratory Disease. 2015 Sep 1;3(5):313-9, https://doi.org/10.4168/aard.2015.3.5.313.

4. Delgado- Dolset MI, Obeso D, Rodríguez- Coira J, Tarin C, Tan G, Cumplido JA, Cabrera A, Angulo S, Barbas C, Sokolowska M, Barber D. Understanding uncontrolled severe allergic asthma by integration of omic and clinical data. Allergy. 2022 Jun;77(6):1772-85, https://doi-org.libproxy.utdallas.edu/10.1111/all.15192.

5. Ross MK, Yoon J, van der Schaar A, van der Schaar M. Discovering pediatric asthma phenotypes on the basis of response to controller medication using machine learning. Annals of the American Thoracic Society. 2018 Jan;15(1):49-58, https://doi.org/10.1513/AnnalsATS.201702-101OC.

6. Khasha R, Sepehri MM, Mahdaviani SA. An ensemble learning method for asthma control level detection with leveraging medical knowledge-based classifier and supervised learning. Journal of medical systems. 2019 Jun;43:1-5, https://doi-org.libproxy.utdallas.edu/10.1007/s10916-019-1259-8.

7. Campo P, Rodríguez F, Sánchez-García S, Barranco P, Quirce S, Pérez-Francés C, Gómez-Torrijos E, Cárdenas R, Olaguibel JM, Delgado J. Phenotypes and endotypes of uncontrolled severe asthma: new treatments. Journal of investigational allergology & clinical immunology. 2013.

8. Sacks JD, Stanek LW, Luben TJ, Johns DO, Buckley BJ, Brown JS, Ross M. Particulate matter–induced health effects: who is susceptible?. Environmental health perspectives. 2011 Apr;119(4):446-54, https://doi.org/10.1289/ehp.1002255.

9. Mukherjee A, Agrawal M. A global perspective of fine particulate matter pollution and its health effects. Reviews of Environmental Contamination and Toxicology Volume 244. 2018:5-1, https://doi-org.libproxy.utdallas.edu/10.1007/398_2017_3.

10. Noh J, Sohn J, Cho J, Cho SK, Choi YJ, Kim C, Shin DC. Short-term effects of ambient air pollution on emergency department visits for asthma: an assessment of effect modification by prior allergic disease history. Journal of Preventive Medicine and Public Health. 2016 Sep;49(5):329, 10.3961/jpmph.16.038.

11. Wu J, Zhong T, Zhu Y, Ge D, Lin X, Li Q. Effects of particulate matter (PM) on childhood asthma exacerbation and control in Xiamen, China. BMC pediatrics. 2019 Dec;19:1-1, https://doi-org.libproxy.utdallas.edu/10.1186/s12887-019-1530-7.

12. Zuo B, Liu C, Chen R, Kan H, Sun J, Zhao J, Wang C, Sun Q, Bai H. Associations between short-term exposure to fine particulate matter and acute exacerbation of asthma in Yancheng, China. Chemosphere. 2019 Dec 1;237:124497, https://doi.org/10.1016/j.chemosphere.2019.124497.

13. Park Y, Koo JH, Jeong H, Jung JY, Kim C, Kang DR. Evaluation of an air quality warning system for vulnerable and susceptible individuals in South Korea: an interrupted time series analysis. Epidemiology and Health. 2023 Feb 14:e2023020, https://doi.org/10.4178/epih.e2023020.

14. Bulot FM, Johnston SJ, Basford PJ, Easton NH, Apetroaie-Cristea M, Foster GL, Morris AK, Cox SJ, Loxham M. Long-term field comparison of multiple low-cost particulate matter sensors in an outdoor urban environment. Scientific reports. 2019 May 16;9(1):7497, https://doi.org/10.1038/s41598-019-43716-3.

15. Kim D, Yum Y, George K, Kwon JW, Kim WK, Baek HS, Suh DI, Yang HJ, Yoo Y, Yu J, Lim DH. Real-time low-cost personal monitoring for exposure to PM2. 5 among asthmatic children: Opportunities and challenges. Atmosphere. 2021 Sep 15;12(9):1192, https://doi.org/10.3390/atmos12091192.

16. Bhat GS, Shankar N, Kim D, Song DJ, Seo S, Panahi IM, Tamil L. Machine learning-based asthma risk prediction using IoT and smartphone applications. IEEE Access. 2021 Aug 9;9:118708-15, 10.1109/ACCESS.2021.3103897.

17. Mehiriz K, Gosselin P. Evaluation of the impacts of a phone warning and advising system for individuals vulnerable to smog. Evidence from a randomized controlled trial study in Canada. International Journal of Environmental Research and Public Health. 2019 May;16(10):1817.

18. Van Vliet D, Smolinska A, Jöbsis Q, Rosias P, Muris J, Dallinga J, Dompeling E, Van Schooten FJ. Can exhaled volatile organic compounds predict asthma exacerbations in children?. Journal of breath research. 2017 Mar 1;11(1):016016, https://doi.org/10.3390/ijerph16101817.

19. Finkelstein J, Jeong IC. Machine learning approaches to personalize early prediction of asthma exacerbations. Annals of the New York Academy of Sciences. 2017 Jan;1387(1):153-65, https://doi.org/10.1111/nyas.13218.

20. Tinschert P, Rassouli F, Barata F, Steurer-Stey C, Fleisch E, Puhan MA, Kowatsch T, Brutsche MH. Nocturnal cough and sleep quality to assess asthma control and predict attacks. Journal of asthma and allergy. 2020 Dec 14:669-78, http://doi.org/10.2147/JAA.S278155.

21. Tsang KC, Pinnock H, Wilson AM, Shah SA. Application of machine learning to support self-management of asthma with mHealth. In2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) 2020 Jul 20 (pp. 5673-5677). IEEE, 10.1109/EMBC44109.2020.9175679.

22. Mayampurath A, Ajith A, Anderson-Smits C, Chang SC, Brouwer E, Johnson J, Baltasi M, Volchenboum S, Devercelli G, Ciaccio CE. Early diagnosis of primary immunodeficiency disease using clinical data and machine learning. The Journal of Allergy and Clinical Immunology: In Practice. 2022 Nov 1;10(11):3002-7, https://doi.org/10.1016/j.jaip.2022.08.041.

23. Tsang KC, Pinnock H, Wilson AM, Shah SA. Application of machine learning algorithms for asthma management with mHealth: a clinical review. Journal of Asthma and Allergy. 2022 Jun 29:855-73, https://doi.org/10.2147/JAA.S285742.

24. Patel D, Hall GL, Broadhurst D, Smith A, Schultz A, Foong RE. Does machine learning have a role in the prediction of asthma in children?. Paediatric Respiratory Reviews. 2022 Mar 1;41:51-60, https://doi.org/10.1016/j.prrv.2021.06.002.

25. Soh PW, Chang JW, Huang JW. Adaptive deep learning-based air quality prediction model using the most relevant spatial-temporal relations. Ieee Access. 2018 Jun 22;6:38186-99, 10.1109/ACCESS.2018.2849820.

26. Phan DV, Yang NP, Kuo CY, Chan CL. Deep learning approaches for sleep disorder prediction in an asthma cohort. Journal of Asthma. 2021 Jul 3;58(7):903-11, https://doi.org/10.1080/02770903.2020.1742352.

27. Blackley SV, Salem A, Zhou L. Deep learning for detection of drug hypersensitivity reactions. Journal of Allergy and Clinical Immunology. 2023 Mar 15, https://doi.org/10.1016/j.jaci.2023.03.004.

28. Mittal V, Sasetty S, Choudhary R, Agarwal A. Deep-learning spatiotemporal prediction framework for particulate matter under dynamic monitoring. Transportation Research Record. 2022 Aug;2676(8):56-73, https://doi.org/10.1177/03611981221082589.

29. Yang G, Lee H, Lee G. A hybrid deep learning model to forecast particulate matter concentration levels in Seoul, South Korea. Atmosphere. 2020 Mar 31;11(4):348, https://doi.org/10.3390/atmos11040348.

30. Abirami S, Chitra P, Madhumitha R, Kesavan SR. Hybrid spatio-temporal deep learning framework for particulate matter (PM 2.5) concentration forecasting. In2020 International conference on innovative trends in information technology (ICITIIT) 2020 Feb 13 (pp. 1-6). IEEE, 10.1109/ICITIIT49094.2020.9071548.

31. Kinga D, Adam JB. A method for stochastic optimization. International conference on learning representations (ICLR) 2015 May 7 (Vol. 5, p. 6).