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RESEARCH ARTICLE

A Proposal for a Predictive Model for the Number of Patients with Periodontitis Exposed to Particulate Matter and Atmospheric Factors Using Deep Learning

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Background: Particulate matter (PM) has been extensively observed due to its negative association with human health. Previous research revealed the possible negative effect of air pollutant exposure on oral health. However, the predictive model between air pollutant exposure and the prevalence of periodontitis has not been observed yet. Therefore, this study aims to propose a predictive model for the number of patients with periodontitis exposed to PM and atmospheric factors in South Korea using deep learning.

Methods: This study is a retrospective cohort study utilizing secondary data from the Korean Statistical Information Service and the Health Insurance Review and Assessment database for air pollution and the number of patients with periodontitis, respectively. Data from 2015 to 2022 were collected and consolidated every month, organized by region. Following data matching and management, the deep neural networks (DNN) model was applied, and the mean absolute percentage error (MAPE) value was calculated to ensure the accuracy of the model.

Results: As we evaluated the DNN model with MAPE, the multivariate model of air pollution including exposure to $PM_{2.5}$, PM_{10}, and other atmospheric factors predict approximately 85% of the number of patients with periodontitis. The MAPE value ranged from 12.85 to 17.10 (mean±standard deviation=14.12±1.30), indicating a commendable level of accuracy.

Conclusion: In this study, the predictive model for the number of patients with periodontitis is developed based on air pollution, including exposure to $PM_{2.5}$, PM_{10}, and other atmospheric factors. Additionally, various relevant factors are incorporated into the developed predictive model to elucidate specific causal relationships. It is anticipated that future research will lead to the development of a more accurate model for predicting the number of patients with periodontitis.

Key Words: Air pollutants, Deep learning, Oral health, Particulate matter, Periodontitis

Introduction

1. Background

Air pollution has become a major global issue because it is correlated with the environment and human living activity. Fine particulate matter ($PM_{2.5}$) which consists of particles smaller than 2.5 μm in aerodynamics diameter, has been extensively researched due to its association with various adverse health effects. Concordantly, a 10 μm or less particulate matter (PM_{10}) is also observed to be potentially nocive to human health due to its ability to penetrate deep into the lungs[1)]. Exposure to fine PM has been linked to respiratory and cardiovascular diseases, including asthma, depression, as well as respiratory and cardiovascular problems[2-6)]. In addition, PM generally composed of sulfur dioxide[7)], carbon monoxide[8)], nitrogen dioxide[9)], and heavy metals, along with other atmospheric substances like ozone[10)], collectively play a role in affecting human health.

While most of the research has been concentrated on

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respiratory and cardiovascular effects, there is growing evidence suggesting that PM may also have implications for oral health[11-13]. Studies have indicated that PM exposure can exacerbate respiratory disease, indirectly impacting oral health due to the interconnected nature of respiratory and oral systems[14]. Moreover, the potential risk of air pollution becoming a modifiable risk factor for periodontal disease has also been observed in Asian countries[12,13]. Periodontal disease is well-known as a chronic inflammatory condition affecting the tooth-supporting structures. It is characterized by pathologic loss of periodontal ligament and alveolar bone[15]. Further, this condition is caused by periodontal pathogens and is observed to be influenced by genetic, environmental, and microbial factors[16].

Deep learning (DL) is revolutionizing industries. Its ability to produce more precise results than conventional approaches is one of its most notable advantages[17]. Additionally, the computational power required for deep neural networks (DNN) is significantly larger than that for conventional methodologies.

The structure of DNN is non-linear and more complex than the conventional methodologies[17]. Subsequently, the accuracy of methodologies depends on the hyperparameters such as the number of learning and the unit of learning. Moreover, it requires the same dependent and independent variables as the conventional ones. In South Korea, fine PM has become a major public issue every year and has been observed to be associated with most health problems[18-21]; however, studies observing the association of air pollution and periodontitis using DL methods have not been observed. Therefore, further investigation on assessing the impact of PM exposure and periodontal disease using DL method is needed.

2. Objectives

This study aimed to propose a predictive model for exposure to PM and other atmospheric factors in relation to the occurrence of periodontitis, based on regional data from South Korea, using DL.

Materials and Methods

1. Ethics statement

This study utilized the secondary data from 2015 to 2022 provided by the Korean Statistical Information Service (KOSIS) and the Health Insurance Review and Assessment (HIRA) databases; therefore, it was approved for review exemption by the Yonsei University Institutional Review Board (IRB Number: 1041849-202401-SB-009-01).

2. Research data

This study is a retrospective cohort design utilizing available data from the KOSIS database (accessed in November 2023) for collecting air pollution in the Korean region. $PM_{2.5}$ and PM_{10} were presented as the average exposure per month in each region. Additionally, the other air pollutant data including sulfur dioxide, ozone, nitrogen dioxide, carbon monoxide and heavy metal concentration are also included (Table 1).

Meanwhile, data of patients with periodontitis (K05) as target variables was extracted from the HIRA database (accessed in November 2023). The number of patients

Table 1. Variables for the DNN-Based Research Model

Category	Variable	Description
Target variable	NPP	Number of periodontitis patients
Input variable	FPM	Concentration of $PM_{2.5}$
	PM	Concentration of PM_{10}
	SO	Concentration of sulfur dioxide
	O	Concentration of ozone
	NO	Concentration of nitrogen dioxide
	CO	Concentration of carbon monoxide
	PB	Concentration of lead
	CD	Concentration of cadmium
	CR	Concentration of chromium
	CU	Concentration of chromium
	MN	Concentration of manganese
	FE	Concentration of iron
	NI	Concentration of nickel
	AS	Concentration of arsenic
	BE	Concentration of beryllium
	AL	Concentration of aluminum
	CA	Concentration of calcium
	MG	Concentration of magnesium

DNN: deep neural networks, PM: particulate matter.

with periodontitis was taken from the number of patients who visited the hospital or clinic and were diagnosed with periodontitis by dental professionals (Table 1). The database does not provide any identifier of patients; hence, no personal information is revealed in this study.

3. Research methodology

All the data were collected and managed in the Microsoft Excel program. After organizing the data, the DNN model was run to assess the predictive model using Python. The DNN model used in this study is designed to propose the impact of air pollution on the number of patients with periodontitis. The DNN model is a type of machine-learning algorithm that mimics the structure and function of the human brain to identify patterns and relationships in data. It consists of interconnected nodes or neurons that process information and can learn from data by adjusting the connections between nodes.

In this study, the DNN model was set up with specific hyperparameters to optimize its performance. The batch size, which determines the number of data points the models processes before updating the model weights, varied from 1 to 10. The number of epochs, which represents the number of times the entire dataset is passed forward and backward through the neural network, ranged from 1 to 10,000. The DNN model was run multiple times to ensure the optimal configuration. Mean absolute percentages error (MAPE) was calculated to evaluate the prediction accuracy of the model the following formula.

$$MAPE_i = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{A_i - P_i}{A_i}\right| \quad (1)$$

A_i: actual value, P_i: predicted value

Table 2. Data Characteristic of Air Pollution in South Korea from 2015 to 2022

Variable (unit)	Min～max	Mean±standard deviation
Number of periodontitis patients	3,495～719,205	124,321±153,449
$PM_{2.5}$ (μg/m^3)	0～47	21.000±8,080
PM_{10} (μg/m^3)	0～88	38.860±13.190
Sulfur dioxide (ppm)	0～0.012	0.003±0.001
Ozone (ppm)	0～0.062	0.029±0.010
Nitrogen dioxide (ppm)	0～0.040	0.017±0.007
Carbon monoxide (ppm)	0～1	0.448±0.127
Heavy metal concentration (μg/m^3)		
Lead (Pb)	0～0.180	0.017±0.014
Cadmium (Cd)	0～0.016	0.001±0.001
Chromium (Cr)	0～0.053	0.003±0.003
Copper (Cu)	0～0.139	0.014±0.012
Manganese (Mn)	0～0.178	0.025±0.022
Iron (Fe)	0～4.661	0.493±0.388
Nickel (Ni)	0～0.050	0.003±0.004
Arsenic (As)	0～0.362	0.004±0.010
Beryllium (Be)	0～0.001	0.000±0.000
Aluminum (Al)	0～2.346	0.175±0.225
Calcium (Ca)	0～2.555	0.374±0.411
Magnesium (Mg)	0～1.218	0.116±0.121

PM: particulate matter.

Results

1. Descriptive statistics

After extracting the related data from the database, the characteristics of air pollution including $PM_{2.5}$ and PM_{10} were described as shown in Table 2. It can be seen that the average of $PM_{2.5}$ and PM_{10} exposure in every region was 21.00 μg/m^3 and 38.86 μg/m^3, respectively. Meanwhile, the number of patients with periodontitis was around 124,321 people per month in each region. Furthermore, the average PM concentration and percentage of patients with periodontitis by year and region are presented in Fig. 1 and 2. The results indicated that the average exposure to $PM_{2.5}$ and PM_{10} decreased, while the number of patients

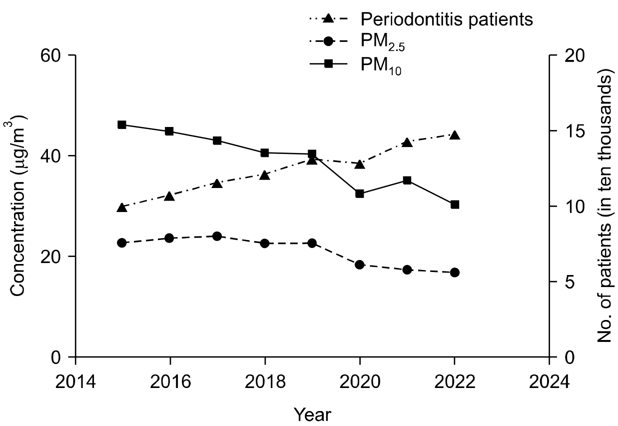

Fig. 1. Average of particulate matter (PM) concentration (μg/m^3) and number of periodontitis patients in South Korea in 2015~2022.

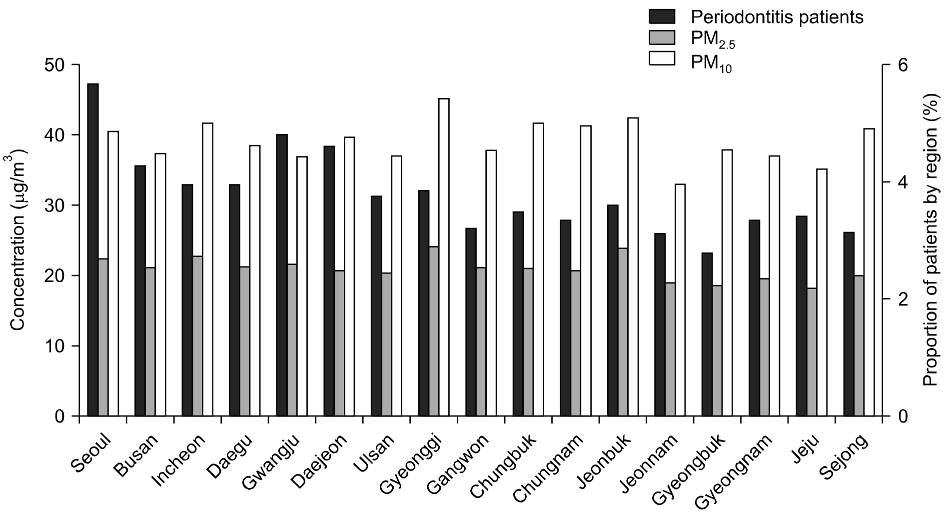

Fig. 2. Average of particulate matter (PM) concentration (μg/m^3) and proportion of periodontitis patients (%) in South Korea based on region in 2015~2022.

Table 3. Evaluation Results of DNN Model

Test	MAPE value
1st	17.10
2nd	13.71
3rd	14.75
4th	12.85
5th	15.25
6th	13.91
7th	12.87
8th	13.12
9th	13.73
10th	13.92
Mean	14.12
Standard deviation	1.30
Min	12.85
Max	17.10

DNN: deep neural networks, MAPE: mean absolute percentage error.

with periodontitis increased from 2015 to 2022.

2. Results from the DNN model

MAPE was calculated to evaluate the prediction result of this research model. To ensure the accuracy of the model, the DNN model was evaluated 10 times with one batch size setting and 10 epochs. The results of this calculation are shown in Table 3, and it appeared that the MAPE value ranged from 12.85 to 17.10, implying that the prediction accuracy reached 85%. The standard deviation was 1.30, which is considered a stable model.

According to Lewis[22], a predictive model with an MAPE value ranging from 1% to 10% is considered as having highly accurate prediction, 11% to 20% is a good prediction, 20% to 50% as a reasonable prediction, while an MAPE value of more than 50% is considered as an inaccurate prediction.

Discussion

1. Interpretation and comparison with previous studies

This study aimed to propose a predictive model for the number of patients with periodontitis exposed to PM and atmospheric factors in South Korea using DL. A study by Li et al.[6] suggested that conducting studies across different geographic locations and over longer periods to confirm the interaction effects and understand the variability across different climates and population is necessary. Moreover, expanding the research to include interactions with other pollutants, such as ozone or nitrogen dioxide, to understand the combined effects of multiple air pollutants is also recommended. Therefore, in this study we included air pollution data over 8 years in the South Korean region and considered other air pollutant data in the same period.

Air pollution consists of many components including $PM_{2.5}$ and PM_{10}, which have a diameter that can enter the respiratory system. These particles are considered foreign particles that can trigger an imbalance condition among the systems. As a part of general health, oral health is also projected to be affected by exposure to air pollution. Environmental pollutants such as PM and air pollution increase the risk of periodontal and respiratory disease, causing chronic inflammation and damage to respiratory and oral tissues[14,23].

The results of previous studies suggest the possible association between PM exposure and periodontitis occurence[12,13,24]. Air pollution could be a potential modifiable risk factor as it can induce biomarkers of inflammation and lead to periodontitis. However, it was difficult to determine this association based on the data collected during this study period. From 2020 to 2022, significant changes occurred in various sectors such as industry, economy, and tourism due to the Coronavirus disease 2019 (COVID-19) pandemic. COVID-19 control actions limiting human activity such as social distancing and lockdown resulted in improving air quality, indicated by the reduction of $PM_{2.5}$ and PM_{10} concentration especially in Seoul and Daegu during the pandemic situation[25]. Following the pandemic regulation, external factors such as reduced factory operation rates and decreased vehicular traffic contributed to a decrease in $PM_{2.5}$ and PM_{10} concentrations[26]. Moreover, the regulation and new habit of wearing masks after the COVID-19 pandemic could also contribute to reducing the inhalation of $PM_{2.5}$ and PM_{10} through the respiratory and oral systems[27,28]. It is believed that these factors could have influenced the outcomes.

Through the research we found that the DNN-based model predicted the number of patients with periodontitis in 85% accuracy by considering the exposure to PM and atmospheric factors. Periodontitis is the result of bone destruction, which is caused by a localized inflammation process in the alveolar bone. In line with the current finding, studies in Taiwan and China also showed that people who were exposed to higher levels of air pollutants in the long-term have a greater risk of periodontitis[13,24]. Marruganti et al.[12] suggested that air pollution is a potential modifiable risk factor for periodontitis, with direct exposure to pollutants potentially leading to increased local inflammation and oxidative stress in periodontal tissue. Furthermore, systemic inflammation and alterations in the oral microbiome possibly appear as the indirect effect of air pollution exposure. Moreover, exposure to $PM_{2.5}$ and nitrogen dioxide may contribute to systemic inflammation and oxidative stress, which could lead to an increased risk of periodontal disease[24]. These findings urge the importance of environmental policies in reducing the burden of periodontitis as well as other non-communicable diseases.

Nevertheless, it should be noted that in the current study, we only included the public data of atmospheric data including $PM_{2.5}$ and PM_{10} and the number of patients with periodontitis, without involving any other individual factors such as socio-demographic, lifestyle, or behavior. This action may confound our study results of the prediction model. Similar machine-learning studies utilizing data at individual levels might perform a more comprehensive model of predictive results[29,30]. The present study could serve as a basis for future exploration of developing a predictive model for periodontal disease.

2. Conclusions

In this current research, we suggested the predictive model for the number of patients with periodontitis exposed to PM and atmospheric factors in South Korea. By collecting available data on air pollution on the KOSIS website and the number of patients with periodontitis from the HIRA website using DNN, it found that the multivariate model of air pollution including exposure to $PM_{2.5}$ and PM_{10} predicted approximately around 85% of the number of patients with periodontitis. The MAPE value ranged from 12.85 to 17.10, which was considered a good performance.

3. Limitations and recommendation

Variables that were involved in this current study were limited due to data availability on the related website; hence, we did not observe the relationship between air pollution and the number of patients with periodontitis. Therefore, we suggested adding some related variables that possibly affect periodontitis occurrence for future studies. For instance, socio-economic, oral health behavior, lifestyle factors including smoking behavior and alcohol consumption, as well as the presence of systematic diseases. In addition, further research using other methodologies and their comparison is also recommended to find which model could predict periodontitis occurrence accurately. Additionally, various relevant factors were incorporated into the developed predictive model to elucidate specific causal relationships. It is expected that future research will lead to the development of a more accurate model for predicting the number of patients with periodontitis.

Notes

Conflict of interest

No potential conflict of interest relevant to this article was reported.

Ethical approval

This research received review exemption from Yonsei University Institutional Review Board (IRB Number: 1041849-202401-SB-009-01).

Author contributions

Conceptualization: Septika Prismasari and Jung Yun Kang. Data acquisition: Septika Prismasari and Hye Young Mun. Formal analysis: Septika Prismasari and Kyuseok Kim. Supervision: Jung Yun Kang. Writing–original draft: Septika Prismasari. Writing–review & editing: Septika Prismasari, Kyuseok Kim, and Jung Yun Kang.

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Data availability

The data used in this study can be accessed and downloaded from the Korean Statistical Information Service database (https://kosis.kr/index/index.do) and Health Insurance Review and Assessment (https://opendata.hira.or.kr/).

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