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Original Article

IMPACTS OF AIR POLLUTANTS ON CHILDREN'S HEALTH: A PREDICTIVE APPROACH BASED ON NEURAL NETWORKS

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Abstract. Air pollution is an environmental factor that affects children's health from pregnancy and continues throughout their development. This pollution constitutes a major public health issue for children. Children’s respiratory and immune systems are still developing, making them particularly vulnerable to environmental pollutants. Their high respiratory rates and greater exposure further increase this vulnerability. This article examines the effects of major pollutants on child health by integrating a predictive modeling approach using artificial neural networks. This model makes it possible to anticipate the impact of pollutants and guide environmental policies for better protection of children.

Keywords: Air pollution, Children's health, Vulnerability, Artificial neural networks, Environmental policy.

INTRODUCTION Several studies have addressed the vulnerability of children to air pollution. This pollution impacts their health in different ways, including effects on respiratory and neurological disorders, which can compromise their overall development. Various air pollutants are responsible for a wide range of respiratory and neurological diseases. Through an analysis of the most common pollutants and their health impacts, using artificial neural networks, it is possible to establish predictive models to analyze and anticipate these effects in order to optimize public health interventions [1]. This study aims to highlight the need for concerted action to protect the health of younger generations.

Main Air Pollutants and Their Effects on Children

The air pollutants of greatest concern to children are listed in Table 1, along with their main sources, specific health effects, and estimated health impact severity.

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These pollutants interact with children's physiological development and amplify the likelihood of chronic respiratory diseases, allergies, and effects on neurodevelopment. These pollutants are widely studied in scientific literature for their adverse effects on child health [2]. Also, these pollutants can have immediate and long-term effects on children's health, including increasing the risk of chronic diseases in adulthood.

Pollution Sources: Road traffic, heating, and industry are the main culprits. Although emissions have decreased, pollution levels remain dangerous.

School Environment: Improving the air quality around schools and kindergartens can reduce children's exposure to pollutants.

Adult Responsibility: Children cannot protect their own health or influence environmental policies. It is up to adults to act.

Local Solutions: Establishing clean air zones around schools, reducing traffic, using less polluting transport, and improving the design of school buildings are among

Polluant µg/m³	Main source	Effects on children's health	Level of nuisance
Fine particles (PM2.5, PM10| µg/m³ (mass concentration of fine particles).	Traffic, heating, industry	Reduced lung function, asthma, respiratory infections	Very high
Nitrogen dioxide (NO_2)	Vehicle emissions, industry	Respiratory tract irritation, aggravation of asthma	High
Ozone (O_3)	Chemical reactions in air, sunlight	Lung irritation, decreased breathing capacity	Moderate
Volatile organic compounds (VOCs)	Household chemicals, industry	Neurological disorders, respiratory irritation	Moderate
Volatile organic compounds (VOCs)		Irritation des voies respiratoires, toux, diminution de la fonction pulmonaire	Élevé
Carbon monoxide (CO)	Incomplete combustion (heating, vehicles)	Reduced blood oxygenation, neurological effects	High

Table 1. The air pollutants of greatest concern to children

measures that can limit children's exposure to air pollution.

Biological Mechanisms of the Impact of Pollutants

The mechanisms of toxicity of these pollutants in children include respiratory and systemic inflammation. Fine particles penetrate deep into the lungs, causing a chronic inflammatory response. Oxidative stress promoted by nitrogen dioxide and ozone is the cause of the production of free radicals and damage to lung and brain cells. Exposure to carbon monoxide reduces oxygen supply to the brain, causing cognitive and neuronal development characterized by cerebral hypoxia. Also, prolonged exposure to sulfur dioxide and fine particles harms lung growth and increases the risk of chronic respiratory diseases [3,4,5].

Data Collection:

We utilized a dataset encompassing 1,200 pediatric patients from urban hospitals in the Setif region, Algeria, collected between 2019 and 2023.

Inclusion Criteria:

- Children age 0 to 12 years old
- Documented respiratory and neurological health assessments

Exclusion Criteria:

- Chronic diseases unrelated to pollution
- Incomplete or missing health data

Health Indicators:

The health indicators used in this study were extracted from clinical records and validated medical histories to ensure accuracy. These include:

- Forced expiratory volume in one second (FEV_1) measured via spirometry
- Frequency of clinically diagnosed asthma attacks
- Neurodevelopmental scores based on standardized clinical tests.

These indicators were extracted from clinical records and validated medical histories to ensure accuracy.

Predictive Modeling Using Neural Networks

Model Objective

The objective of the model is to predict the effects of air pollutants on child health based on air quality data and health indicators [6,7].

Model Architecture

The neural network used is a feedforward neural network, optimized to process environmental and medical data. The artificial neural network is designed with the following structure:

- Input Layer: This layer consists of 10 features, integrating air pollutant concentrations (PM2.5, PM10, NO2, O3, VOCs, CO) alongside demographic variables (age, sex).
- Hidden Layers: The network employs three hidden layers with 32, 16, and 8 neurons respectively. Rectified Linear Unit (ReLU) activation functions are applied in these layers to introduce non-linearity.
- Output Layer: A single linear neuron generates a composite health risk index, which is a continuous score representing the overall health risk to the child.

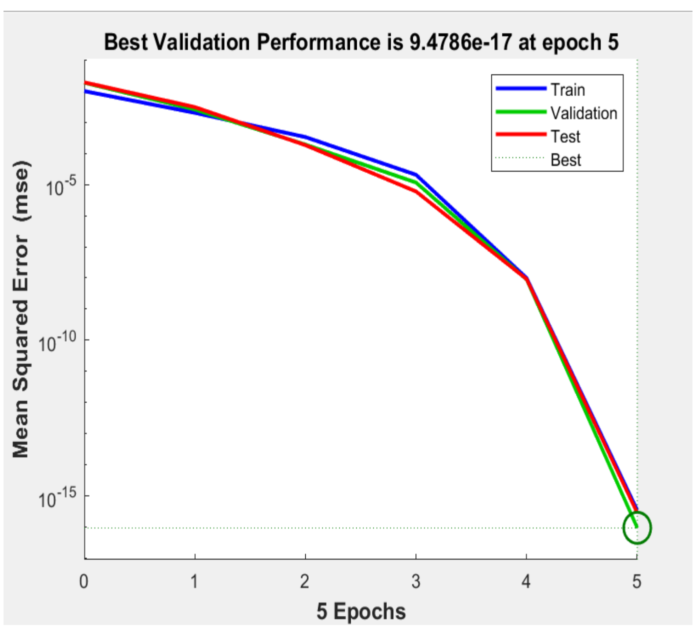
Training Process

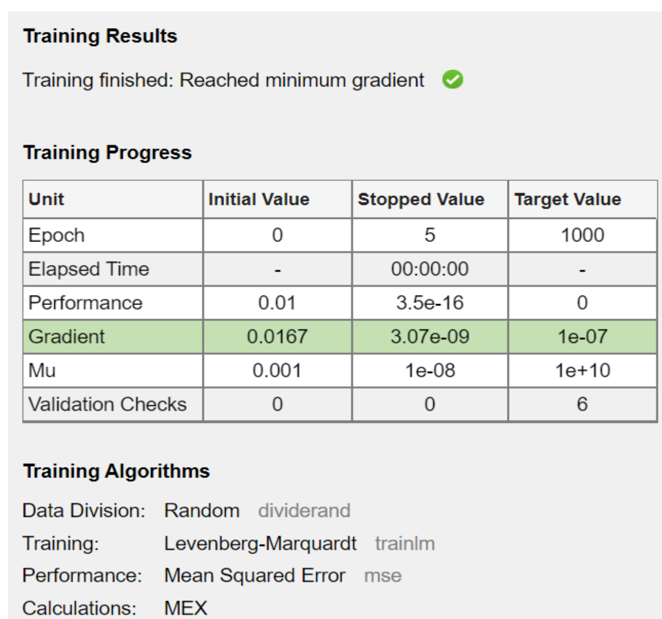
Training was performed over 100 epochs with a 70% training to 30% validation split, optimizing weights using the Levenberg-Marquardt algorithm. The dataset was further divided for evaluation as follows: 70% for Training, 15% for Validation, and 15% for Testing. The Mean Squared Error (MSE) was used as the cost function to minimize prediction errors. Model performance was evaluated based on gradient analysis and overall performance metrics. The Levenberg-Marquardt algorithm was chosen for its rapid convergence and efficiency on moderate-sized datasets, making it suitable for health-related applications.

RESULTS

Performance Analysis

Figure 1 illustrates the performance of the system, showing the evolution of the mean squared error (MSE) over epochs. The error gradually decreases, indicating effective learning by the network. The best validation performance was achieved at epoch 5, with an MSE of 9.4786e-17. This extremely low error value suggests an excellent model fit. The consistent decrease in error indicates a well-trained model without overfitting, as evidenced by the validation and test error curves closely following the training error curve. This demonstrates good generalization ability and high accuracy due to minimal errors.





Training Results

Training finished: Reached minimum gradient

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	5	1000
Elapsed Time	-	00:00:00	-
Performance	0.01	3.5e-16	0
Gradient	0.0167	3.07e-09	1e-07
Mu	0.001	1e-08	1e+10
Validation Checks	0	0	6

Training Algorithms

Data Division: Random dividerand
Training: Levenberg-Marquardt trainlm
Performance: Mean Squared Error mse
Calculations: MEX

Figure 1. Network Performance.

This graph displays the Mean Squared Error (MSE) across training, validation, and test sets over 5 epochs. The best validation performance is observed at epoch 5 with an MSE of 9.4786e-17, indicating strong model convergence and low error.

Figure 2 shows the distribution of the network training data through an error histogram. The histogram, which reflects the distribution of errors (MSE), shows values highly concentrated near zero, signifying good model convergence. The gradient histogram, representing the variations used to adjust network weights, is strongly concentrated towards very low values, indicating model stabilization. The Mu values, which illustrate the evolution of the adaptation parameter, sharply decrease over epochs, meaning the algorithm found a good direction for optimization. Convergence is successful, as most values in the histograms are close to zero, confirming that training proceeded well without excessive error. A homogeneous distribution of gradients indicates effective weight updates and minimal need for major adjustments, underscoring the model's stability [8].

This histogram shows the frequency distribution of errors (Targets - Outputs) for the training, validation, and test sets, centered around zero, signifying good model performance.

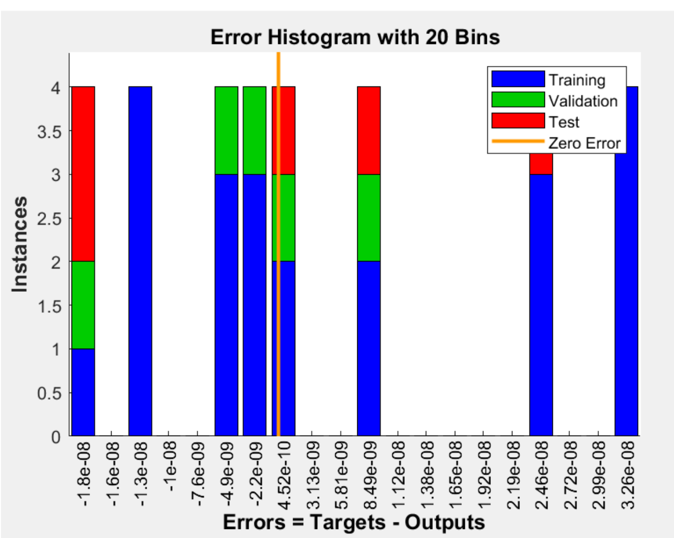


Figure 2. Distribution of data from network training.

The training process, utilizing the Levenberg-Marquardt algorithm (trainlm), stopped after 5 epochs, demonstrating its rapid convergence and efficient optimization. The Mean Squared Error (MSE) ranged from an initial value of 0.01 to a final value of 3.5e-16, indicating near-zero error and excellent predictive ability. The gradient increased from 0.0167 to 3.07e-09, which is very small by the end, signifying model stabilization. The Mu (adaptation parameter) increased from 0.001 to 1e-08, corresponding to a constant decrease, indicating smooth optimization.

The health index produced is a continuous composite score that encapsulates respiratory and neurological health risks based on weighted combinations of normalized clinical indicators: Forced Expiratory Volume in one second (FEV1), asthma attack frequency, and neurodevelopmental test scores. These weights are optimized during the training process. Validation was conducted using an independent subset of the data, demonstrating strong agreement with clinical assessments. Additional external validation against independent clinical cohorts remains planned. Validation checks remained at 0, meaning no stops due to overfitting were encountered, a sign of good practice.

Implications for Public Health

Our neural network model provides a promising approach for early detection and risk stratification of pollution-related health risks in children. With further external validation and transparency improvements, it could be integrated into public health monitoring and clinical decision support systems [9].

Policies and Prevention Measures

Strategies to reduce children's exposure to pollutants include improving air quality around schools (low-emission zones, greening). To limit automobile pollution, it is necessary to optimize transportation and urban infrastructure. Environmental regulations should also be considered to reduce industrial and domestic emissions. Health monitoring and awareness campaigns should also be implemented to inform families and policymakers.

Limitations

Despite promising results, this study has some limitations. We can cite the limitations related to the dataset that was collected in a specific urban region (Setif, Algeria), which could limit the generalizability of the results to other geographical areas with different pollution profiles, socioeconomic conditions, or health systems. Also, although the model incorporates the main air pollutants and demographic variables, it may not take into account all potential environmental or individual factors that influence child health, such as genetic predispositions, nutritional status, or indoor air quality. Finally, as an initial predictive model, further external validation with larger and more diverse datasets is essential to confirm its robustness and applicability in various clinical and public health settings.

CONCLUSION The impact of air pollutants on children's health is a health emergency requiring targeted interventions and strengthened regulation. The application of artificial intelligence to environmental issues paves the way for preventive and reactive policies to protect the most vulnerable populations [10]. A predictive model based on artificial neural networks could be integrated into air quality monitoring tools to reduce children's exposure to pollution and prevent respiratory and neurological diseases [11].

Declarations

Conflicts of interest

The authors declare that they have no competing interests.

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