The Impact of Pollen on the Human Respiratory System: An Intelligent Analysis Using Artificial Neural Networks

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*Abstract***.** For plant fertilization, pollen, a fine powder, is released. This is necessary for plant reproduction. The problem is that this has implications for human respiratory health. This involves immunological mechanisms. This study presents the analysis of the effects of pollen on the respiratory system from the perspective of processing epidemiological data as an environmental influence using artificial intelligence techniques, particularly artificial neural networks. Since the interaction between exposure to allergenic pollens and immune responses is complex and difficult to analyze using conventional methods, artificial neural networks are suitable for this purpose. The results of this analysis highlight allergic rhinitis, asthma exacerbations, and the lengthening of the pollen season induced by climate change.

Key words. Pollen, Plant reproduction, Human respiratory, Artificial Intelligence, ANN

Received: April 24, 2024. Revised: January 26, 2025. Accepted: May 29, 2025. Published: July 31, 2025.

1. Introduction

The reproductive vector of many angiosperms and gymnosperms is pollen, which occurs as natural particles suspended in the air. Although pollen grains are essential for biodiversity, they are powerful allergens that cause hypersensitivity reactions in sensitive individuals. The proportion of individuals with these hypersensitivities to pollen is considerable, representing some 40% of the world population [1]. In a context of climate change and the increasing prevalence of allergic diseases, it is becoming necessary to understand the impact that pollen has on the respiratory system.

Given the complex interaction between environmental exposure and immune responses, the use of artificial intelligence tools becomes useful. In this regard, machine learning systems, particularly artificial neural networks, are suitable [2]. The influence of pollen-related parameters on allergic sensitivity is analyzed by artificial neural networks in this study.

2. Mechanisms of Pollen-Induced Respiratory Responses

2.1 Allergenic Properties of Pollen

Pollen action occurs via various proteins and glycoproteins. IgE of the immune systems in susceptible individuals has the ability to recognize these molecules. Examples of these molecules are Bet v 1 (from birch), Phl p 5 (from timothy) and Amb a 1 (from ragweed) [3].

2.2 Immune Response Pathway

Dendritic cells in the respiratory mucosa capture pollen allergens upon inhalation. Allergenic peptides are presented by these cells to naive T lymphocytes, which differentiate into Th2 lymphocytes. The class change of B lymphocytes is mediated by Th2 cytokines (e.g., IL-4, IL-5, IL-13) for the production of allergen-specific IgE antibodies. These antibodies bind to highaffinity receptors present on mast cells and basophils. This step is considered preparation for future exposure. Indeed, upon subsequent exposure to the same allergen, it leads to cross-linking of IgE molecules, which triggers the release of mediators such as histamine, leukotrienes, and prostaglandins. This compound reaction causes inflammation and increased vascular permeability, mucus hypersecretion, and bronchoconstriction. These are the characteristic signs of allergic rhinitis and asthma [4].

3. Clinical Manifestations

3.1 Allergic Rhinitis (Hay Fever)

Allergic rhinitis is characterized by nasal congestion, sneezing, rhinorrhea, and itchy eyes. This allergy mainly affects adults (up to 30% of cases) and children (up to 40% of cases) worldwide. This often-seasonal allergic rhinitis is a consequence of the effect of plant pollen. The peaks of these symptoms are reached during certain pollination periods [5].

3.2 Asthma Exacerbations

Pollen-induced inflammation of the respiratory tract and bronchial hyperreactivity are much more pronounced in asthmatics. This observation is observed in hospital emergency rooms. It has been recorded that the number of consultations for these asthmatic cases increases with the increase in pollen concentration [6].

3.3 Other Respiratory Effects

Recent studies report that pollen may contribute to several other health effects. Pollen-related disorders such as chronic cough, sinusitis, and even non-allergic irritant reactions have been reported in some individuals. Adding to this, the resulting ultrafine particles of pollen may penetrate deeper into the lungs. This even gives rise to systemic inflammatory reactions [7].

4. Environmental and Climatic Influences

4.1. Climate change significantly modulates pollen dynamics

The effects of climate change are multiple. It can be noted that higher temperatures lead to an extension of pollen seasons with earlier and prolonged pollen release. This release is not only prolonged, but also increases production. High CO_2 levels promote plant growth and therefore allergen concentrations. Also, the disruption of precipitation patterns and temperature distribution across geographic areas causes changes in the distribution of allergenic species. This will result in the introduction of new allergens in new geographic areas.

From this perspective, it becomes necessary to adopt new strategies for allergy forecasting through planning at the level of public health authorities. In this context, our study helps establish a predictive model integrating various factors involved in the process [8],[9].

5. Materials and Methods

5.1 Study Design and Dataset Description

This study aims to investigate the relationship between pollen-related parameters and allergic responses using an artificial neural network (ANN) model. The database includes environmental, demographic, and clinical data related to allergy severity, expressed on a scale of 1 to 6 (Pollen Sensitivity Degree – PSD).

Table 1. Summary of Input and Output Variables

Column		Description
Pollen_Count	(PC)	Pollen concentration (grains/m³)
AQI	(AQI)	Air Quality Index
Temperature	(T)	°C
Humidity	(H)	% Relative Humidity
Wind Speed	(W.S)	km/h
Precipitation	(P)	mm/day
Season	(S)	1=Spring, 2=Summer, 3=Fall
Geographic Location	(G.L)	0=Urban, 1=Rural
Age	(A)	1=Child, 2=Teen, 3=Adult, 4=Senior
Gender	(G)	0=Female, 1=Male
Family History of Allergies	(F.H.A)	0=No, 1=Yes
Personal History of Allergies Diagnosed	(P.H.A)	0=No, 1=Yes
Smoking Status	(S.T)	0=Non-smoker, 1=Smoker
Medication Use	(M.U)	0=No, 1=Yes
Time Spent Outdoors Occupation	(T.S.O)	Hours per day
Occupation	(OC)	0=Office worker, 1=Outdoor worker
Respiratory Health Baseline	(R.H.B)	FEV1% predicted
Exposure to Indoor Allergens	(E.I.A)	0=Low, 1=High
Stress Levels	(S.L)	1–10 scale
Sleep Quality	(S.Q)	1–10 scale
Pollen Sensitivity Degree	(P.S.D)	Output variable (1–6 scale: mild to severe)

The dataset was divided into training, validation and test subsets. The data distribution method is random data. The output variable used in this study is the pollen sensitivity degree (PSD), this variable is considered as an indicator of prediction to the ANN model.

5.2 Artificial Neural Network Architecture and Training Methodology

An artificial neural network (ANN) was used to model the complex interactions between the input and output variables (DSP). The ANN architecture was designed as a multi-layer feedforward perceptron, trained using the Levenberg-Marquardt algorithm (trainlm), which is particularly suited for rapid convergence in small to medium-sized datasets. The mean squared error (mse) was used as a performance function to optimize training [10].

The artificial neural network was implemented using the MATLAB Neural Network Toolbox, where the training process was monitored using key indicators such as gradient descent, elapsed epochs, and performance values. As shown in Figure 1, the network reached its minimum gradient threshold after four epochs, indicating effective training. The initial performance value of 6.19 decreased to 3.74×10^{-17}, demonstrating excellent model accuracy. The gradient value also fell below the stopping criterion of 1×10^{-7}, confirming convergence.

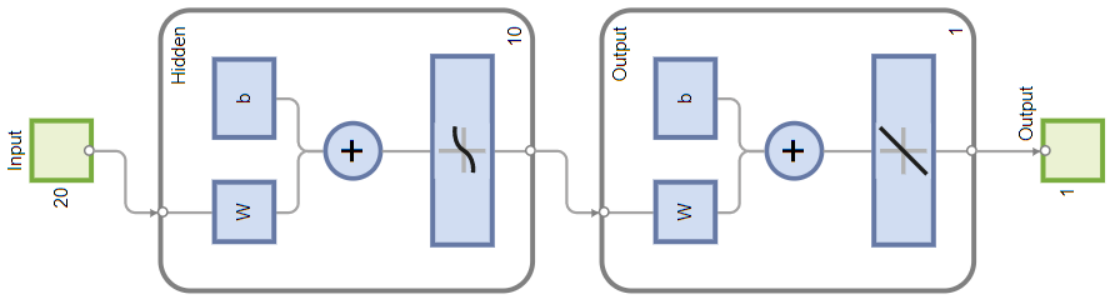

Figure 1. Network architecture

Figures 2 and 3 illustrate the learning progression and performance of the ANN model over successive epochs. Figure 2 plots the learning, validation, and testing curves, showing that all three runs converge to minimal error, suggesting that the model generalizes well to unobserved data without significant overfitting. This is also confirmed by the validation tests, which remained within acceptable limits (reaching a maximum of one test before stopping).

5.3 Interpretation of Results

Training Results

Training finished: Reached minimum gradient

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	4	1000
Elapsed Time	-	00:00:11	-
Performance	6.19	3.74e-17	0
Gradient	26.1	2.95e-08	1e-07
Mu	0.001	1e-07	1e+10
Validation Checks	0	1	6

Training Algorithms

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

Figure 2. Training progress

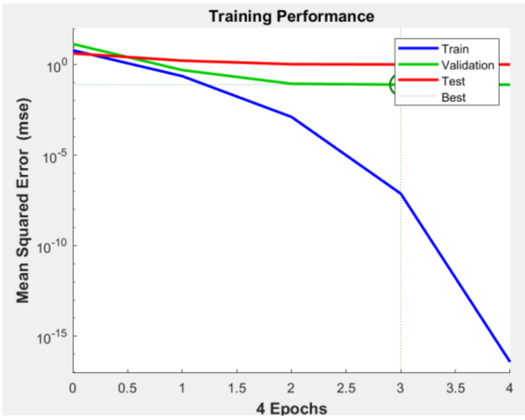

Figure 3. Correlation between predicted and actual outputs

Figure 3 presents the correlation between the predicted and actual outputs across different data subsets, highlighting the model's ability to accurately predict the degree of sensitivity to pollen based on the input parameters. A strong linear relationship indicates high predictive power, making this model suitable for identifying key drivers of allergic responses.

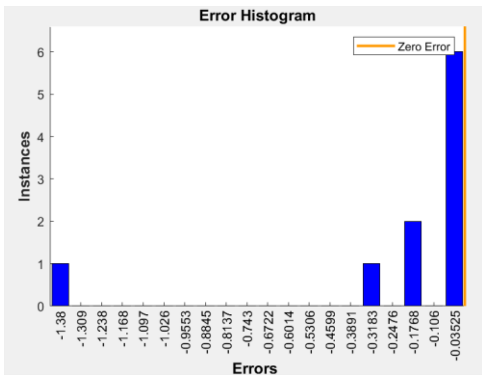

Figure 4. Error histogram

Figure 4 shows the error histogram, which demonstrates that the model performs exceptionally well, with a significant number of perfectly accurate predictions (zero error). The error distribution is centered around zero, indicating low bias and high reliability.

6. Discussion

The results demonstrate that the ANN model effectively captured the nonlinear relationships between environmental, demographic, and clinical factors and pollen sensitivity. The successful convergence and low error rates suggest that the selected variables are significant predictors of allergic response severity. Furthermore, the use of the Levenberg-Marquardt algorithm ensured fast and stable learning, making it an ideal choice for this application.

A notable limitation of this approach lies in its reliance on the quality and representativeness of the input data. Although the current model performed well, future work could expand the dataset size and incorporate additional variables, such as air pollutant concentrations or genetic markers, to improve generalizability. Furthermore, cross-validation with independent datasets could strengthen the robustness of the results.

7. Future Directions

The integration of multi-omics (genomics, proteomics, metabolomics), AI-based modeling, and personalized medicine will revolutionize pollen allergy management. Precision allergen immunotherapy, tailored to individual molecular profiles, combined with real-time exposome monitoring using wearable sensors, promises a paradigm shift in preventive care [9].

8. Conclusion

Pollen remains a major environmental driver of allergic respiratory disease, with significant impacts on individual health and societal well-being. Its effects are mediated by complex immunological pathways and are increasingly influenced by global climate change. Through interdisciplinary collaboration between immunology, climatology, data science, and public health, we can develop innovative strategies to reduce the burden of pollen-related respiratory disease and improve quality of life worldwide.

This study highlights the utility of artificial neural networks (ANNs) for modeling the complex dynamics of allergen responses, providing insight into how environmental and personal factors interact to influence allergic sensitivities. These models can be valuable tools for public health planning, enabling personalized risk assessments and targeted interventions for individuals with varying degrees of pollen sensitivity.

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