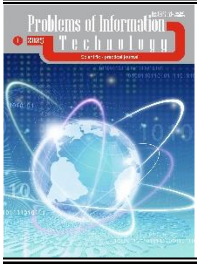

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Research of the influence of ecological factors on bronchial asthma crisis using artificial intelligence methods

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ABSTRACT

When examining the dynamics of inflammatory allergic upper respiratory diseases, including the factors affecting the onset of crises in bronchial asthma patients in particular, it becomes clear that the severity and duration of the situation, which reduces the quality of life and work capacity, directly depends on the characteristics of the environmental environment in which the patient is, i.e., allergens in the air, air pollution, industrial emissions and humidity coefficient, and factors such as observed hot weather conditions. The above-listed factors, functions, and constant coefficients were included in the mathematical model established to measure the severity of the crisis in bronchial asthma patients. The continuous coefficients representing the degrees of impact were determined based on the established a fully connected feedforward deep neural network model, and an approximate solution of the resulting system of differential equations was found using the Runge-Kutta 4th order method.

1. Introduction

Bronchial asthma is a prevalent chronic respiratory condition that significantly affects human health globally. Environmental variables play a significant role in the onset and worsening of this condition. Among the causes of the development and exacerbation of this disease, environmental factors are of particular importance. These factors have multifaceted mechanisms of action, such as air pollutants, various types of allergens, temperature and humidity changes, as well as the state of the immune system. The complex and multiparameter nature of bronchial asthma necessitates various methodological approaches in its modeling.

In recent years, various mathematical, cybernetic and computational methods have been applied to analyze and predict the relationship between asthma and environmental factors. Among them, statistical

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models, classical differential equation systems, nonlinear dynamics methods and neural networks occupy a key place. Neural networks and artificial intelligence technologies are considered a promising approach to more accurately reflect the complex nonlinear nature of the disease and the mechanisms of action of environmental factors. However, existing models mainly use empirical parameters and often cannot fully cover the dynamics in the real environment. At the same time, the accuracy and reliability of traditional numerical methods used to solve differential equations have not been sufficiently investigated.

Our main goal in this research work is to propose a more effective methodological approach by applying artificial intelligence-based approaches and high-precision numerical methods to model and predict bronchial asthma crises related to environmental factors.

The rest of the paper is organized as follows. Section 2 describes the literature review. The mathematical model that determines the dynamics of the severity of bronchial asthma attacks in patients with current environmental factors is given in section 3. Section 4 analyses the prediction of coefficients representing the impact levels of environmental factors using a built-in neural network. Analytical solution of the system of differential equations under consideration is given in section 5. Also, numerical solution of the system of differential equations is given in section 6. Section 7 analyses the experimental results, as well as a comparison of the analytical and numerical solution of the equations. Section 8 draws the conclusions and outlines the directions for future research.

2. Related work

Various methodological approaches have been used to study the relationship between asthma and environmental factors. A study by Custovic and Woodcock (2014) highlighted the impact of environmental allergens on asthma symptoms. Guarnieri and Balmes (2014) extensively analyzed the impact of air pollutants on asthma attacks. There are various studies using neural networks and other artificial intelligence techniques. For example, Papi et al. (2018) studied the immunological aspects of asthma and discussed the potential of artificial intelligence techniques. In addition, Calderón et al. (2016) noted that house dust allergens play an important role in the development of asthma attacks.

However, most of the existing studies lack sufficient accuracy in modeling nonlinear relationships and there is little comparison between traditional approaches used to solve systems of differential equations and analytical solutions. Our contribution in this study is to perform parameter estimation with artificial intelligence-based deep learning methods and apply the Runge-Kutta 4th order method to solve the system of differential equations with high accuracy. This approach we propose provides higher accuracy and reliability in predicting bronchial asthma attacks.

Summing up the above works, the main contributions of our work are summarized as follows:

- Utilization of advanced neural network-based methodologies to accurately predict differential equation parameters.
- Application of the fourth-order Runge-Kutta numerical method to solve the differential equations with maximum accuracy.
- Comprehensive validation of numerical solutions through direct comparison with analytical solutions, ensuring the reliability of model predictions.
- Provision of a robust methodological framework that can significantly enhance the accuracy and reliability of predicting bronchial asthma crises influenced by environmental factors, thereby offering a solid foundation for future scientific investigations.

3. Mathematical model of the asthama crises dynamics

This section describes the mathematical model of the asthma crises dynamics. Let us introduce the following notation: We can formulate a mathematical model that relates the severity of a bronchial asthma patient's crisis to environmental factors such as airborne allergens, industrial emissions, and other factors of this type (3-4) as the following (1-2) system of ordinary differential equations:

$$\begin{cases} \dfrac{dI(t)}{dt} = \alpha R(t) + \beta N(t) + \gamma I(t), & I(t) \in [0, I_{max}], t \ge 0 \\ \dfrac{dR(t)}{dt} = -\delta R(t) + \eta, & R(t) \in [0, R_{max}], \quad t \ge 0 \\ \dfrac{dN(t)}{dt} = -\lambda\left(N(t) - N_{max}\right), & N(t) \in [N_{min}, N_{max}], t \ge 0 \end{cases} . \quad (1)$$

$$I(t_0)=I_0,\ R(t_0)=R_0,\ N(t_0)=N_0, \quad (2)$$

$$\alpha,\beta,\gamma,\delta,\lambda\in[0,1], \quad (3)$$

$$\eta\in[0,R_{\max}]. \quad (4)$$

where, $I(t)$ is chosen as an upper bound function expressing the severity of the patient's crisis over time. $R(t)$ is an upper bound function expressing the change in airborne allergens over time; $N(t)$ is a lower and upper bound function expressing the degree of influence of environmental factors on the severity of the crisis.

Also, α - allergens, β - industrial emissions, γ - constant coefficients representing the degrees of influence of the immune system in the termination of the crisis are shown. Other constant coefficients in the $(1-2)$ system, δ - the rate of decrease of airborne allergens, η - the rate of increase of airborne allergens. The degree of convergence of factors is expressed by λ.

4. Predicting impact rates by using neural network model

For the numerical and analytical solution of the system of differential equations (1) under consideration, we need to find predicted value of the coefficients $\alpha,\beta,\gamma,\delta,\lambda,N_{\max}$, which are used in (1) system modeling the impact of environmental factors on bronchial asthma crises by constructing neural network model.

When preparing the dataset necessary for conducting the experiment, factors such as allergen concentration in the air (Custovic and Simpson), that shows the values between 150-200 particles/m³ are indicative of moderate to high exposure levels; environmental pollution level (Guarnieri and Balmes), which includes the values between 33-42 µg/m³ represent typical urban air pollution levels; immune response index (Holgate), that it has scaled between 0.7-0.8, representing heightened immune activity; temperature (D'Amato et al.) and humidity (Arundel et al.) were taken into account.. The selection of these factors and their corresponding coefficients was adapted to medical (Anna M. Zhang et al.), ecological research (Lotfata A. et al.), physiological research and existing mathematical-cybernetic modeling literature. The additional parameters for dataset are illustrated in Table 1.

Table 1. Description of the experimental dataset

Dataset	Number of samples	Number of features
Synthesized dataset	500	11

After preprocessing the dataset, model architecture to be built follows a fully connected feedforward deep neural network (DNN) structure optimized using KerasTuner for hyperparameter tuning.

Optimizer for this DNN model is chosen by Adam (Adaptive Moment Estimation) as it combines RMSprop (Root Mean Square Propagation) and Momentum SGD (Stochastic Gradient Descent) for adaptive learning rates during trainings and efficacious convergence. This optimization algorithm handles sparse data well by dynamically adjusting learning rates and also converges faster than traditional SGD. Alternatively, SGD and RMSprop were considered but rejected due to slower convergence and lower adaptability to non-stationary data. The additional informations for DNN are illustrated in Table 2 and Table 3.

Table 2. Description of the layers of the neural network model

Layer	Type	Activation	Units
Input_layer (Batch Normalization, Droput 0.2)	Dense	ReLU	128
Hidden_layer_1 (Batch Normalization, Droput 0.2)	Dense	ReLU	64
Hidden_layer_2	Dense	ReLU	64
Output_layer	Dense	Linear	6

Table 3. Used parameters and storage during model training

Total parameter	Trainable parameter	Non-trainable parameter	Optimizer parameter
26 088	25 446	640	2
101.96 KB	99.40 KB	2.50 KB	12.00 B

In this model, the activation function used in hidden layers is ReLU (Rectified Linear Unit) as it prevents the vanishing gradient problem, is computationally efficient. The output layer uses a linear activation function since the model predicts continuous numerical values, making it the most suitable choice for regression tasks. Also, learning rate for this model has set to $\mu = 0.001$.

During training-testing process, split ratio has set to 80% training and 20% testing (Pareto Principle) to ensure a balanced dataset, preventing test set overfitting while maintaining training efficiency. A smaller test set (e.g., 10%) would increase test overfitting, while a larger test set (e.g., 30%) would reduce training efficiency.

In addition, DNN model evaluation is based on Mean Absolute Error (MAE) and Mean Squared Error (MSE) approaches. MAE provides an intuitive measure of absolute error magnitude and is less sensitive to outliers, while MSE penalizes large errors more, making it useful for emphasizing significant deviations.

Fig 1. show the loss of model that optimized in the course of epochs.

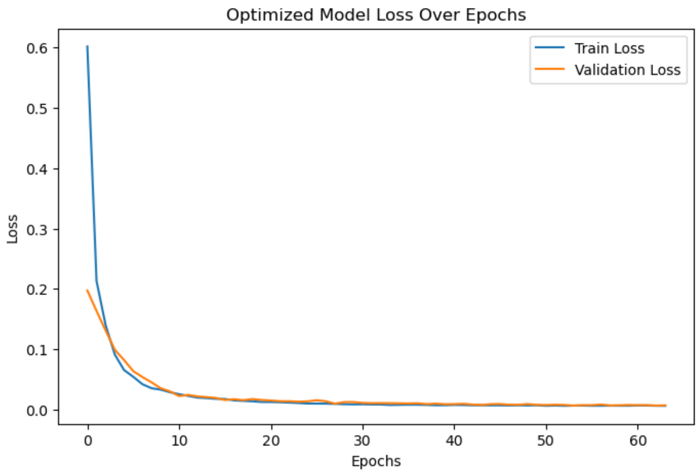

Fig. 1. Optimized model loss over epochs

Estimated values of each $\alpha, \beta, \gamma, \delta, \lambda$ coefficient were predicted using the constructed deep neural network. Also, the error rates between the true values in the given dataset and the values that we have obtained were shown in Table 4.

Table 4. Predicted values and errors of the coefficients

Coefficient	Predicted value	True value	MAE / MSE
α	0.344648	0.358102	0.023347 / 0.000906
β	0.198435	0.208331	0.020968 / 0.000661
γ	0.317736	0.327657	0.017049 / 0.000438
δ	0.267455	0.294940	0.095291 / 0.12725
λ	0.168006	0.175215	0.059405 / 0.004827
$N_{\max}$	0.934140	0.998585	0.104231 / 0.016334

5. Analytical solution of the differential equation system

As can be seen, the second equation of the system of differential equations (1) is a differential equation that can be separated into its variables. Therefore, this equation can be separated into its variables in the following way:

$$\frac{1}{\delta}\frac{d(\delta R(t)-\eta)}{\delta R(t)-\eta} = -dt \tag{5}$$

or,

$$\frac{d(\delta R(t)-\eta)}{\delta R(t)-\eta} = -\delta\, dt\,. \tag{6}$$

After integrating both sides of equation (6), the following next equation is obtained:

$$R(t) = \frac{c}{\delta}e^{-\delta t} + \frac{\eta}{\delta}\,. \tag{7}$$

The integral constant included in equation (7) is found as follows within the initial condition - $R(0) = R_0$:

$$c = R_0 \delta - \eta . \quad (8)$$

By writing equation (8) in (7), $R(t)$ – the upper bound function characterizing the change in airborne allergens over time – is defined as follows:

$$R(t) = R_0 e^{-\delta t} - \frac{\eta}{\delta}(e^{-\delta t} - 1) . \quad (9)$$

In the same way, after integrating the third equation of system (1) within the initial condition - $N(0) = N_0$, $N(t)$ - the function bounded from below and above, which determines the degree of influence of environmental factors on the severity of the crisis, is defined as follows (10),

$$N(t) = N_{\max} - (N_{\max} - N_0)e^{-\lambda t} . \quad (10)$$

In the next stage, we have made the following $\xi = \frac{\eta}{\delta}, \chi = \frac{c}{\delta}$ and $N_{\max} - N_0 = k$ substitutions.

In particular, by writing relations (9) and (10) in the first equation of the system of equations (1), the following differential equations (11) and (12) are obtained, which depend on the unknown function $I(t)$ - the patient's crisis severity over time,

$$\frac{dI(t)}{dt} = \alpha(\chi e^{-\delta t} + \xi) + \beta(N_{\max} - ke^{-\lambda t}) + \gamma I(t) , \quad (11)$$

$$\frac{dI(t)}{dt} - \gamma I(t) = \alpha(\chi e^{-\delta t} + \xi) + \beta(N_{\max} - ke^{-\lambda t}) . \quad (12)$$

To integrate equation (12), $I(t)$ – the function expressing the severity of the patient's crisis over time – can be expressed as the product of two functions,

$$I(t) = U(t)V(t) . \quad (13)$$

By substituting equation (13) into equation (12), we obtain equation (14),

$$\begin{aligned} U(t)\frac{dV(t)}{dt} + V(t)\left[\frac{dU(t)}{dt} - \gamma U(t)\right] = \\ = \alpha\left(\chi e^{-\lambda t} + \xi\right) + \beta\left(N_{\max} - ke^{-\lambda t}\right) \end{aligned} . \quad (14)$$

We find the function $U(t)$ from equation (15) in the form (16).

$$\frac{dU}{dt} - \gamma U = 0, \quad (15)$$

$$U(t) = e^{\gamma t} . \quad (16)$$

After substituting (16) into equation (14), the function $V(t)$ is found in the form (17).

$$\begin{aligned} V(t) = -\frac{\alpha\chi}{\delta+\gamma}e^{-(\delta+\gamma)t} + \frac{\beta k}{\lambda+\gamma}e^{-(\lambda+\gamma)t} - \\ -\frac{\alpha\xi + \beta N_{\max}}{\gamma}e^{-\gamma t} + c \end{aligned} . \quad (17)$$

Then writing (16) and (17) in (13), the function $I(t)$ is defined as (18) within the initial condition $I(t_0) = I_0$.

$$\begin{aligned} I(t) = -\left[\frac{\alpha\chi}{\delta+\gamma} + \frac{\alpha\xi + \beta N_{\max}}{\gamma} - \frac{\beta k}{\lambda+\gamma} + I_0\right]e^{\gamma t} - \\ -\frac{\alpha\chi}{\delta+\gamma}e^{-\delta t} + \frac{\beta k}{\lambda+\gamma}e^{-\lambda t} - \frac{\alpha\xi + \beta N_{\max}}{\gamma} \end{aligned} . \quad (18)$$

6. Numerical solution of the differential equation system

In our research work, it was decided to use the four-stage Runge-Kutta (RK4) method to solve the system of differential equations describing the dynamics of bronchial asthma attacks. The main reason for choosing this method is the nonlinear nature of the analyzed system and the high accuracy requirements during the solution.

In general, since analytical solutions of systems of differential equations are complex and in some cases impossible, numerical methods are resorted to. Among these methods, Runge-Kutta methods are widely used, and the most widely used among them is the RK4 method.

The RK4 method is a method that allows you to approximate the solution trajectory with high accuracy by performing four separate calculations at each step. The basics of the method were put forward by German mathematicians C. Runge and M.W. Kutta. The application of the method consists in evaluating the right-hand side of the equation at various intermediate points at each step. As a result, the average value is calculated from these evaluations and the solution for the next step is found. This process significantly reduces error, allowing for highly accurate solutions to equations. In the Table 5 below shows a comparative analysis of numerical solution methods for nonlinear ordinary differential equations.

Table 5. Description of the analysis of numerical solution methods for nonlinear ordinary differential equations.

Method	Accuracy	Stability	Suitability for nonlinear ODE
Euler`s method	$O(h^2)$	Poor	Not suitable
Runge-Kutta 2nd Order	$O(h^3)$	Moderate	Moderate
Runge-Kutta 4th Order	$O(h^5)$	High	Best
Runge-Kutta-Fehlberg	Adaptive	High	Overkilling problem

7. Experimental results

The proposed approaches were implemented on Intel(R) Core(TM) i5-10300H with quad-cores running at 2.50 GHz and 8 GB RAM. The experiments were conducted in Jupyter Notebook environment via Python 3.

The values of the coefficients predicted by DNN were substituted into the formula (18) obtained during the analytical solution of the considered nonlinear differential equations (1). Here, the values of $I(t)$ - the upper-bound function expressing the severity of the patient's crisis over time, $R(t)$ - the function indicating the change in allergens in the air over time, and $N(t)$ - the function measuring the degree of influence of environmental factors on the severity of the crisis, which are limited from below and above, were found within the initial conditions $I(t)=0.5, R(t)=0.3$ and $N(t)=0.7$.

As a result of the analytical experiment we have obtained $I(t)=0.953061, R(t)=0.315949$ and $N(t)=0.733164$ final values, that contains the more exact solution.

During the solution by numerical methods, the results were realized in the iterative process with a step $\tau=0.1, t_n=n\tau, \varpi_\tau=\{t\in(0,T],0\le\tau\le1\}$. The initial conditions for the functions were applied with the conditions specified in the analytical solution. Table 6 shows the values of the functions found by the numerical method and the values found by the analytical method after 10 iterations, and then the error was estimated.

Table 6. Numerical solution of the function that determines the severity of the patient's crisis

Step	I(t) analytical	I(t) numerical	Absolute error
t=0.1	0,953061	0,500000	0.453061
t=0.2	0,953061	0,541254	0.411807
t=0.3	0,953061	0,584002	0.369059
t=0.4	0,953061	0,628289	0.324772
t=0.5	0,953061	0,674163	0.278898
t=0.6	0,953061	0,721672	0.231389
t=0.7	0,953061	0,770866	0.182195
t=0.8	0,953061	0,821799	0.131262
t=0.9	0,953061	0,874522	0.078539
t=1	0,953061	0,929093	0.023968

In Fig. 2, the graphical representation of the upper bound function $I(t)$ - which expresses the severity of the patient's crisis over time - is shown, which is searched based on the values of the system of equations (1) found analytically and numerically. When analyzing the graphical representation, we can see that the approximation is quite sufficient and the error margin is low.

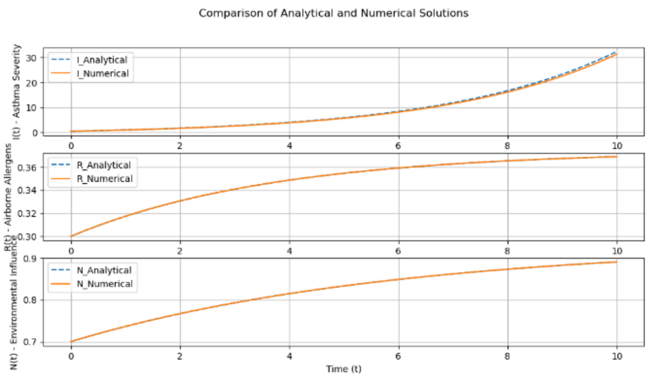

Fig 2. Comparison of the analytical and numerical solution

8. Conclusion and future works

Within the framework of this research work, a new approach based on artificial intelligence was presented to assess the impact of environmental factors that play a significant role in the occurrence and development of bronchial asthma attacks. In our study, a system of differential equations was constructed based on real medical and ecological data, and the coefficients of these equations were estimated with high accuracy using a modern neural network method. Then, based on the estimated coefficients, the system was solved both analytically and numerically (RK4) and a comparative analysis of both solutions was conducted. The results showed that the presented approach is effective, stable and reliable for predicting asthma attacks. The obtained results can play an important role in the management of asthma and improving the quality of life of patients.

In the future, it is possible to use the results of this research work in wider practical applications, especially in the field of biomedical engineering. Thus, the modeling results obtained here can play a key role in the creation of "smart masks" that can be used for the early detection of bronchial asthma attacks in real time, which are new generation medical technologies. Such masks can continuously measure changes in environmental factors, identify potential asthma attacks in real time and provide the patient with an early warning system.

In addition, the application of special mobile or portable devices that can be developed based on this model is also envisaged. These devices can constantly analyze the risk factors present in the patient's environment, predict possible asthma attacks and provide warnings to patients to take preventive measures. For the future, the research will include clinical trials of this approach and its application on real patients. It is also planned to test the model on larger-scale and more complex datasets, which will further increase the accuracy and reliability of the proposed method.

As a result, in the future, this approach will stimulate the development of innovative, patient-oriented medical devices and equipment in both medicine and engineering, and will lay the foundation for new solutions that will significantly improve the living conditions of asthma patients.

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