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Integration of physiological factors into a mathematical model of the human eye condition

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ABSTRACT

Mathematical models of the human eye serve as adaptive tools for analyzing and predicting ophthalmological parameters, considering their interrelations and individual patient characteristics. Their application in ophthalmology enhances the quality of diagnostics, monitoring, and treatment, ultimately improving patients' quality of life. The developed eye condition model is based on a mathematical function that integrates physiological eye parameters, each assigned a weight coefficient to determine its impact on the overall condition index. The model accounts for complex nonlinear interactions between parameters, allowing for a more accurate representation of physiological processes. To optimize the weight coefficients, the L-BFGS-B method is employed—an iterative algorithm that efficiently minimizes the loss function and ensures high accuracy in adapting the model to individual patient data.This model offers several advantages: it enables early diagnosis of diseases such as glaucoma, cataracts, and macular degeneration, tailors treatment plans based on individual patient parameters, and facilitates disease monitoring and progression prediction for timely therapy adjustments. Furthermore, the model can be integrated with modern technologies, including virtual and augmented reality systems, as well as artificial intelligence for automated diagnostics. Thus, the proposed mathematical model serves as a universal tool for analyzing eye conditions and developing innovative diagnostic and therapeutic technologies. By incorporating parameter interdependencies and their effects on the physiological state of the eye, it provides ophthalmologists with a powerful instrument for enhancing diagnostics, prediction, and disease monitoring in vision healthcare.

Keywords: Human eye; mathematical modeling; integral index; nonlinear dependencies; optimization methods; adaptability; monitoring; prediction

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INTRODUCTION

Mathematical models of eye health are essential tools in ophthalmology, offering advanced IT solutions for the diagnosis, monitoring, and treatment of eye diseases [1, 2], [3]. These models are applied in the following areas.

- **Early Diagnosis**: Automated detection of diseases at early stages improves treatment outcomes [3, 4].
- **Monitoring**: Tracking chronic diseases helps assess therapy effectiveness and adjust treatment plans [5, 6].
- **Personalized Approach**: Adaptive models account for individual patient characteristics to optimize treatment.
- **Enhanced Precision**: Modeling reduces risks during surgical interventions [6].
- **Scientific Research**: Studying physiological processes facilitates the development of new diagnostic methods [7]. .
- **Cost Optimization**: Automation reduces unnecessary medical procedures, increasing healthcare system efficiency.

Models incorporating parameters such as intraocular pressure, visual field index, and perfusion pressure allow for predicting the risk of glaucoma and other diseases [8, 9], [10].

The integration of machine learning algorithms enhances diagnostic personalization and fosters the implementation of advanced IT solutions in ophthalmology [8, 11].

1. ANALYSIS OF LITERARY DATA AND PROBLEM STATEMENT

1. **Diagnosis and Vision Correction**: Models improve diagnostic accuracy and enable personalized treatment, particularly in analyzing visual impairments and accommodation.

However, their application requires high-quality data and expert interpretation [8, 12].

2. **Prediction of Retinal Diseases**: Predictive models for retinal pathologies enhance diagnosis and therapy but require data standardization and solutions for interpretation challenges [13, 14], [15].

3. **Modeling Visual Processes**: Computational models of eye-brain interactions are used in diagnosing visual disorders and developing computer vision technologies.

However, their progress is limited by computational costs and generalization difficulties [16, 17], [18].

4. **Vision Correction and Restoration**: Laser vision correction based on mathematical models increases procedure safety.

Key challenges include the complexity of biological processes and high computational requirements [17].

5. **Age-Related Vision Changes**: Models analyzing age-related changes facilitate early diagnosis and personalized treatment but demand precise data across age groups and consideration of complex biological processes [19, 20].

6. **VR/AR Technologies**: Integrating models with virtual and augmented reality systems expands diagnostic and treatment capabilities, facing challenges in computational demands [17].

7. **Eye Movement Dynamics**: These models are valuable in medicine and VR/AR interaction technologies. Their effectiveness is growing with advances in machine learning and improved tracking accuracy [17].

8. **Intraocular Pressure and Heat Exchange Models**: These assist in predicting diseases and personalizing treatment but require validation and improved data quality [21, 22].

Thus, developing a universal mathematical model of the eye that considers a wide range of physiological and external factors remains a pressing task. Such models can integrate data to improve diagnosis, prediction, and treatment of ophthalmological diseases [23, 24].

The aim is to develop an adaptive mathematical model of the human eye to predict ophthalmic diseases, improve diagnostic accuracy, optimize treatment and improve the quality of life of patients.

To achieve this objective, the following tasks are set:

- **develop a comprehensive model** that integrates key ophthalmological parameters and accounts for nonlinear dependencies;
- **analyze complex interactions** between physiological parameters (e.g., intraocular pressure, perfusion, and blood flow) and external factors (e.g., stress, lifestyle, and environmental conditions);
- **optimize model parameters** using advanced numerical methods (L-BFGS-B) to improve prediction accuracy and sensitivity to data variations;
- **ensure adaptability** by incorporating patient-specific characteristics for personalized diagnostics and treatment strategies;
- **enhance practical applicability** by integrating the model with AI-based decision-making systems, visualization tools (VR/AR), and real-time treatment optimization techniques.

2. MAIN RESEARCH RESULTS

The developed mathematical model of the human eye is presented in the form of an integral index of its state (Seye) and is a development of the previously developed model of the eye state [25], in which the integral index Seye is calculated taking into account the non-linearity of parameters and their mutual relations, the weight of each parameter and changes depending on the patient's age, blood flow and other factors. The Seye model describes the eye condition as a function of key parameters

$$\begin{aligned} S_{eye} = k1 \cdot log(IOP+1) + k2 \cdot log(RQ+1) + \\ +k3 \cdot (BCVA-h)^2 + k4 \cdot log(Tr+1) + k5 \cdot \\ \cdot e^{-VF1} + k6 \cdot log(1+Pperf) + k7 \cdot \\ \cdot log\left(1+\frac{\alpha}{t1}\right) + k8 \cdot log(age+1) + \\ +k9 \cdot e^{additional_{factor}}, \end{aligned} \tag{1}$$

where *IOP* is intraocular pressure (normal: 10-21 mmHg, range: 5-60 mmHg); *RQ* is volumetric intraocular blood flow (normal: 3.2-3.5‰, range: 0.5-9.0 ‰); *BCVA* is visual acuity (normal: 1.0, range: 0-2.0); *Tr* is tear production (normal: 10-30 mm, range: 1.0-40.0 mm); *VFI* is visual field index (normal: 100 %); *Pperf* is perfusion pressure (normal: 55-80 mmHg, range: 20-100 mmHg); $\alpha/t1$ is vascular tone of intraocular vessels (normal: 18-20 %, range: 12-35 %); *aditional_factor* is additional factors (lifestyle, diseases, genetics, etc.); $k1 \ldots k9$ are weighting coefficients.

The developed mathematical model of eye health is represented by the integral indicator Seye, which accounts for nonlinear dependencies between parameters, their interrelations, weighting coefficients, as well as age-related and physiological factors.

The model is designed for the quantitative assessment of the influence of various factors on eye health, including individual parameter characteristics. Nonlinearities are described using exponential and polynomial functions based on biological principles and empirical data [26, 27].

The eye health model (1) takes into account fewer factors affecting eye health. This reduces the accuracy

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of determining the state of the eye, and therefore affects the accuracy of diagnosing and predicting its condition.

The new Seye model includes a larger number of factors and their non-linear interactions, which significantly improves the accuracy of prediction compared to the previous version. This approach allows us to create a more accurate and adaptive representation of the model, which is formulated as follows:

$$Seye = k1 \cdot log(IOP+1) \cdot A + k2 \cdot log(RQ+1) \cdot \cdot B + k3 \cdot \left(BCVA - f_{ofcet}\right)^2 \cdot A + k4 \cdot \cdot log(Tr+1) \cdot log(Tr+1) \cdot C + k5 \cdot \cdot e^{-VF1} \cdot A + k6 \cdot log(1+Pperf) \cdot \mathrm{B} + +k7 \cdot log\left(1+\frac{\alpha}{t1}\right) \cdot D + k8 \cdot log(age+1) \cdot E + +k9 \cdot e^{additionai\_factor} \cdot F, \quad (2)$$

where $\mathrm{A} = f(age, disease_{status})$;

$B = g(blood_{pressure}, vascular_{health})$;

$C = h_{env}(environmental_{factor})$;

$D = h_{stress}(stress_{level}, activity_{level})$;

$E = i(life_{style})$;

$F = j(genetic_{factors})$

In the eye condition model (2):

$$f(age, disease_{status}) = 1 + 0.1 \cdot age - 0.05 \cdot disease_{status};$$

$$g(blood_{pressure}, vascular_{health}) = 1 + 0.2 \cdot log(blood_{pressure} + 1) - 0.1 \cdot vascular_{health};$$

$$h_{env}(environmental_{factor}) = 1 + 0.3 \cdot exp(-0.01 \cdot environmental_{factor});$$

$$h_{stress}(stress\_level, activity\_level) = 1 + 0.05 \cdot stress\_level - 0.02 \cdot activity\_level;$$

$$i(life\_style) = 1 + 0.15 \cdot life\_style;$$

$$j(genetic\_factors) = 1 + 0.1 \cdot genetic\_factors.$$

f_{offset} is used to centre the quadratic function in the model. It allows taking into account individual peculiarities of vision. For stabilization of calculations it allows to avoid numerical instability. A fixed value is used.

$$disease_{status} = \sum_{i=1}^{n} \omega_i \cdot d_i,$$

$$blood_{pressure} = \frac{systolic + 2 \cdot diastolic}{3},$$

$$environmental_{factor} = \frac{\sum_{i=1}^{n} \varphi_i \cdot e_i}{\sum_{i=1}^{n} \varphi_i},$$

$$life_{style} = \frac{\sum_{i=1}^{n} \mu_i \cdot l_i}{\sum_{i=1}^{n} \mu_i},$$

$$genetic_{factors} = \sum_{i=1}^{m} g_i \cdot risk_i,$$

where d_i is presence of a specific disease (0-absent, 1-present); ω_i is weighting coefficient reflecting the severity of the disease's impact (glaucoma – ω_1=0.4, diabetic retinopathy – ω_2=0.6); $systolic$ is systolic blood pressure; $diastolic$ is diastolic blood pressure; e_i is specific environmental factor; φ_i is weighting coefficient for each environmental factor; l_i is specific lifestyle characteristic, such as physical activity; μ_i is weighting coefficient for each lifestyle characteristic; g_i is presence of a specific genetic marker (0 or 1); $risk_i$ associated with this marker (0 or 1).

The parameters *IOP*, *RQ*, *BCVA*, and *VFI* vary within normal limits, but their fluctuations significantly affect the condition of the eye [28]. *Tr*, *IOP*, and *Pperf* are critically important for intraocular pressure and blood supply, while age and additional factors modify their influence through weighting coefficients.

Parameter relationships in the model:

- *IOP* ↔ *Pperf*: An increase in intraocular pressure (*IOP*) reduces perfusion pressure (*Pperf*), impairing eye blood supply and increasing the risk of ischemic processes associated with glaucoma;
- *IOP* ↔ *RQ*: High intraocular pressure can impair blood flow in the retina, causing ischaemia and damage to the optic nerve, which is reflected in a decrease in *RQ* (intraocular volumetric blood flow coefficient (e.g. in glaucoma);.
- *Pperf* ↔ *RQ*: Reduced perfusion pressure due to high IOP or low systemic arterial pressure results in reduced ocular blood flow, which worsens intraocular volume blood flow (*RQ*) exacerbating retinal ischaemia (e.g. in glaucoma, diabetes mellitus, retinal vein thrombosis);.
- *BCVA* ↔ *VFI*: Loss of visual fields (*VFI*) is associated with progressive deterioration of visual function, including reduced visual acuity (*BCVA*) (glaucoma, high myopia);
- *age* ↔ *RQ*, *VFI*: With age, there is an exponential decrease in the quality of intraocular volumetric blood flow (*RQ*), which causes a decrease in retinal blood supply and narrowing of visual fields (*VFI*) due to degenerative processes and age-related changes in the vascular system;
- *Tr* ↔ *IOP*: Age has a direct relationship with tear production (*Tr*), and shows that age patients have reduced tear production and develop dry eye syndrome, which adversely affects the quality of life of patients;
- α/*t*1 ↔ *Pperf*, *RQ*: Vascular tone (α/*t*1) directly affects blood flow in the retina by altering intraocular volume blood flow (*RQ*) and *Pperf*, leading to inadequate retinal blood supply and subsequently to degenerative processes on the ocular fundus (glaucoma, retinal degeneration, diabetic retinopathy);
- *aditional_factors* ↔ *IOP*, *RQ*: Stress, lifestyle and other external factors affect both intraocular pressure (*IOP*) and retinal blood supply (*RQ*), altering the overall condition of the eye and affecting patients' quality of life.

These relationships are not only logically justified but also supported by clinical and physiological data. The model accounts for nonlinear interactions between parameters, allowing for the analysis of their influence on eye health and the prediction of changes under various scenarios. These relationships are not only logically justified but also supported by clinical and physiological data. The model accounts for nonlinear interactions between parameters, enabling an analysis of their impact on eye health and the prediction of changes under various scenarios.

The new Seye model (Table 1) incorporates more factors and their nonlinear interactions, significantly improving predictive accuracy compared to the previous version. Previously, a change in intraocular pressure (*IOP*) by 5-10 mmHg or a decrease in visual acuity (*BCVA*) from 1.0 to 0.1 resulted in a sharp deterioration in eye health.

Table 1. **Comparison of eye state models**

Criterion	First Model	Second Model
Complexity	Simple, linear.	Complex, nonlinear.
Interaction Consideration	None.	Yes, through functions f, g, h, i, j.
Additional Parameters	None.	Yes, includes environment, stress, etc.
Prediction Accuracy	Limited, suitable for basic analysis.	High, accounts for more factors.
Data Requirements	Requires fewer data.	Requires more data for training.

***Source:* compiled by the authors**

Now, the influence of these parameters is modified by functions *f*(), *g*(), *h*(), *i*(), and *j*(), which account for age, diseases, and other factors. For instance, in elderly patients with hypertension, an increase in *IOP* has a stronger impact than in younger individuals without comorbidities. Unlike the previous version, where parameters acted independently ($k1$, $k2$,...,$k9$), the new model describes them through interconnected and nonlinear functions.

Exponential dependencies have been introduced to amplify the effects of factors such as vascular tone and blood pressure.

For patients with low perfusion pressure (*Pperf*), these factors are critical, especially for those with hypertension. For the first time, stress, physical activity, and environmental factors are considered through functions *h*(stress_level, activity_level) and *h*(environmental_factor).

For example, in individuals with high stress and low activity levels, a decrease in *BCVA* occurs more rapidly than in active and calm patients.

Additionally, a component *j*(genetic_factors) has been added to account for genetic predisposition: even a slight increase in *IOP* can critically reduce Seye in such patients. Thus, parameter changes no longer produce fixed effects but instead depend on the context, including age, overall health, lifestyle, and genetics. This enhances the model's adaptability but complicates its calibration due to the need to consider individual characteristics in specific conditions. For the purpose of studying the developed new Seye model (2), Python code has been created to group factors within the model based on their physiological and clinical relationships.

The combination of operations (addition and multiplication) allows the model to account for complex interactions. Coefficient optimization helps adapt the model to the data while avoiding artifacts. Robustness against zeroing out factors ensures the model's reliability when working with real-world data. The developed code version includes the following features:

- generation of random parameters within specified ranges;
- data visualization and analysis, including histograms and dependencies;
- optimization capabilities to identify values that minimize or maximize Seye.

This makes the model not just a tool for calculating Seye but a more powerful instrument for in-depth analysis and the study of the influence of multiple factors on eye health.

In the provided code, the *scipy.optimize. minimize* function is used to optimize the coefficients $k1$, $k2$, ... ,$k9$. Key aspects of using *scipy.optimize. minimize* in the code:

Objective Function: The *objective_function* computes the error between the calculated Seye (based on the current coefficients *k*) and the target value Seye,target.

Initial Coefficient Values

Optimization starts with an initial assumption where all coefficients are set to 1:

initial_k = np.ones(9) # Initial coefficient values

Coefficient Constraints

To prevent excessive growth of the coefficients, a range of $0.1 \le ki \le 0.5$

*bounds = [(0.1, 0.5)] * 9*

Optimization Process

The L-BFGS-B method, suitable for constrained optimization tasks, is used. The minimize function takes the objective function, initial coefficients, model parameters, target Seye, and constraints as input.

Optimization Results

The target value *target_Seye* is defined.

- Seye is an integral measure of eye health, obtained from clinical data.
- *Target_Seye* can be set as the average value among healthy patients in the corresponding age group or as a predicted optimal value based on available data.
- Dynamic updates of *target_Seye* are possible if time-series data is used (e.g., for monitoring disease progression).

The optimization is performed.

- During the calibration phase before practical application.
- When adapting to a new patient (e.g., after updating medical data).
- As part of a self-learning process (if the model updates its weights based on new clinical data).

After the optimization process is complete, the following results are obtained:

Optimized coefficient values:

optimized_k = result.x

Calculated Seye value based on the optimized coefficients:

optimized_Seye=calculate_Seye(params, optimized_k)

Thus, scipy.optimize.minimize is applied to minimize the difference between the calculated and target Seye values, ensuring the model adapts effectively to the given data. The developed code expands the capabilities for studying the eye state model Seye. It incorporates permissible parameter ranges, such as IOP (intraocular pressure) from 5 to 60 mmHg and age from 1 to 100 years. This allows simulation of various eye conditions through random variation of input data. Additionally, the code includes an analysis of the Seye distribution, enabling histogram construction and pattern identification.

The optimization of the model's weight coefficients is performed using the L-BFGS-B method from the SciPy library [29, 30], which efficiently handles smooth nonlinear functions using an approximated Hessian matrix. The method minimizes the Seye objective function by defining initial values, parameter bounds (0.1–0.5), and accounting for nonlinear dependencies.

Advantages of the Approach:

- incorporation of nonlinearities through logarithmic, exponential, and quadratic functions;
- optimization of weights to fit a target Seye value;
- constraint enforcement on coefficients prevents incorrect results;
- model adaptability through consideration of age, disease presence, and lifestyle.

The developed code ensures precise optimization of weight coefficients, enhancing the model's flexibility and adaptability.

Fig. 1 illustrates the contour plot of the objective function for the coefficients $k1$ and $k2$ with other parameters fixed.The contour plot illustrates the relationship between the loss function

$$Error = \frac{(Seye - target\_Seye)^2}{target\_Seye^2} \cdot 100\% \qquad (3)$$

and the coefficients $k1$ and $k2$ while keeping other parameters fixed. It helps identify key trends, analyze the impact of parameters on outcomes, and optimize the model. The plot shows levels of the loss function: green areas correspond to minimal error values (optimal model parameters), while purple areas indicate maximum errors (largest deviations).

The error range has been normalized to 0–100%, where 0% corresponds to the minimum deviation and 100% to the maximum observed in the training dataset. This normalization ensures that the error values are expressed in relative terms, making them more interpretable and comparable.

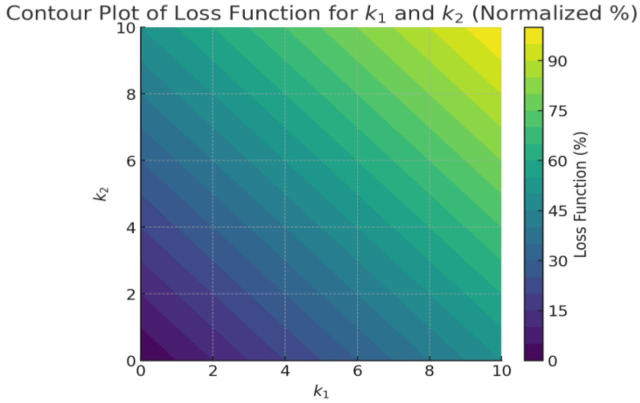

Fig. 1. **Contour plot of the target function for two coefficients k1 and k2**

Source: **compiled by the authors**

The graph axes represent the values of coefficients k_1 (horizontal) and k_2 (vertical), spanning a range of 0–10. Tighter contour lines indicate high model sensitivity to parameter changes. The minimum error value (0%) corresponds to the best parameter settings where Seye ≈ target_Seye, while the maximum error (100%) represents the highest deviation from the target. This plot is essential for determining optimal parameters, assessing loss function sensitivity, and identifying local minima, ultimately improving model precision and stability.

Key Aspects of the Optimization Code

In the developed eye state model code, the section related to the optimization of weight coefficients and the calculated Seye value includes the following critical elements.

1. Objective Function: Defined as *objective_function*, it minimizes the error between the calculated Seye value and the target value.
2. Initial Coefficients: Set to *initial_k* = *np.ones(9)* (all coefficients initialized to 1).
3. Parameter Constraints: Specified using *bounds* to prevent coefficients from exceeding allowable ranges.
4. Optimization: Utilizes the L-BFGS-B method from *scipy.optimize.minimize*.
5. Results: Outputs the optimized coefficients and the calculated Seye value after optimization.

Objective Function Definition and Optimization Algorithm:

The algorithm for optimizing $k1$, $k2$,…,$k9$ using the L-BFGS-B method includes:

- Objective: Minimize the target function by calculating the optimal coefficients $k1$, $k2$,…,$k9$ to determine the eye state while considering nonlinear dependencies of the parameters.
- Algorithm Steps.
  - Initialization.
- Request values for parameters to analyze the eye state (*IOP*, *RQ*, *BCVA*, *Tr*, *VFI*, *Pperf*, *α/t1*, *age*, *additional_factor*).

• Set initial values for the coefficients $k1, k2,\ldots,k9$ (e.g., within the range of 0.1 to 10.0).

• Define constraints on the ranges of $k1, k2,\ldots,k9$.

Each coefficient $k1, k2,\ldots, k9$ is restricted within a range: $a_i \le ki \le b_i$.

This ensures the physical interpretability of the parameters and prevents invalid values.

The method incorporates constraints using gradient projection. At each step, it verifies whether $k1, k2,\ldots,k9$ exceed the boundaries $[a_i, b_i]$. If they do, the current value of ki is projected back into the valid range:

$$ki = proj_{[a_i, b_i]}(ki) - \min(\max(ki, a_i), b_i)$$

A function is defined to calculate the eye state indicator Seye based on input parameters, including coefficients.

To define the objective function.

• Describe the eye state function (calculate_Seye): This function depends on the input parameters and the optimized coefficients $k1, k2,\ldots,k9$. It accounts for nonlinear relationships, such as:

○ Logarithmic dependencies for parameters *IOP*, *RQ*, *Tr*, *α/t1*, and *Pperf*.

○ Parabolic dependencies for visual acuity (*BCVA*).

○ Exponential dependencies for *VFI* and additional_factor.

• Compute the eye state (Seye) considering all parameters.

• Define the objective function for minimization: This function calculates the error or deviation from the ideal eye state value based on the current values of $k1, k2,\ldots,k9$.

The objective function for minimization, aimed at calculating the eye state based on the current coefficients $k1, k2,\ldots,k9$, is as follows:

$$\frac{1}{N}\sum_{i=1}^{N} \left(Seye_{pred}(k1, k2, \ldots k9, a_i) - Seye_{obs,i}\right)^2 \quad (4)$$

where $Seye_{pred}$ is value calculated using the model, including nonlinear dependencies for all parameters; $Seye_{obs}$ represents the reference or observed data; a_i are the model parameters; N is the total number of observations.

Equation (4) minimizes the average error across the entire dataset, allowing the coefficients $k1, k2,\ldots,k9$ to be adapted for accurately describing the eye's state.

Function (4):

• Inputs: Takes coefficients k, a set of parameters, and observed values.

• Process: Calculates Seye, preds for each parameter set, computes the Mean Squared Error (MSE), and returns the MSE value for minimization.

Model Exploration

The model can be studied in several ways.

1. Parameter Variation: By modifying parameters, you can analyze their influence on Seye.

2. Single-Parameter Focus: By fixing all parameters except one, graphs can be created to study individual effects (e.g., how eye condition changes with increasing IOP).

3. Numerical Optimization: You can use optimization to identify parameter ranges where Seye indicates pathology.

4. Extreme Scenarios: Setting boundary values (e.g., maximum IOP and minimum BCVA) allows for evaluating the model's response in critical conditions.

Fig. 2 illustrates the dependency of Seye on intraocular pressure (IOP) with other parameters held constant. The graph confirms the logarithmic nature of this relationship: at low IOP levels, a small increase significantly raises Seye, whereas at higher IOP, the effect diminishes.

Physiological Interpretation:

• Low *IOP* (<5 mmHg): Impairs retinal blood flow, reducing visual function.

• Normal Range (10-21 mmHg): Corresponds to a moderate increase in Seye.

• High *IOP* (>30 mmHg): Accelerates glaucoma progression, though its impact on Seye becomes less pronounced.

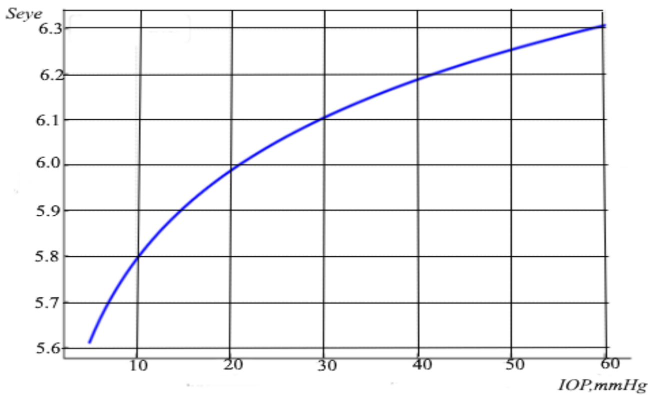

Fig. 2. **Eye Condition Seye Based on Changes in *IOP***

***Source:* compiled by the authors**

The graph demonstrates a smooth curve, validating the model's correctness. Any abrupt changes observed in real-world data might necessitate parameter refinement. Overall, the model accurately represents the impact of *IOP* on eye condition and aligns with clinical observations.

Fig. 3 and Fig.4 show the dependencies of Seye on the Visual Field Index (*VFI*) and volumetric intraocular circulation (*RQ*) under fixed conditions.

The graph in Fig. 3 demonstrates an exponential trend: increasing VFI (0-100 %) leads to a rise in Seye. Low VFI (≈0 %) is associated with pathological conditions (e.g., glaucoma), while high VFI (≈100 %) corresponds to better eye health.

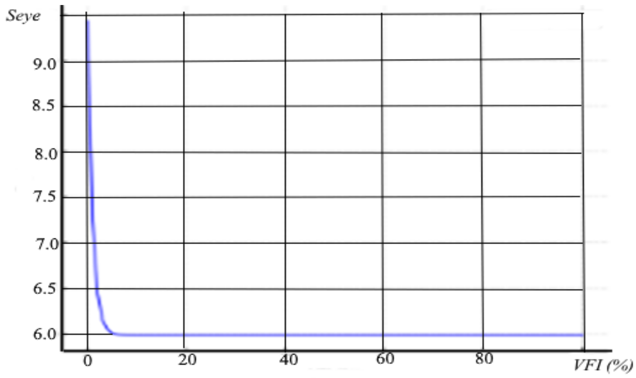

Fig.3. **Seye condition according to the results of *VFI* changes**
Source: **compiled by the authors**

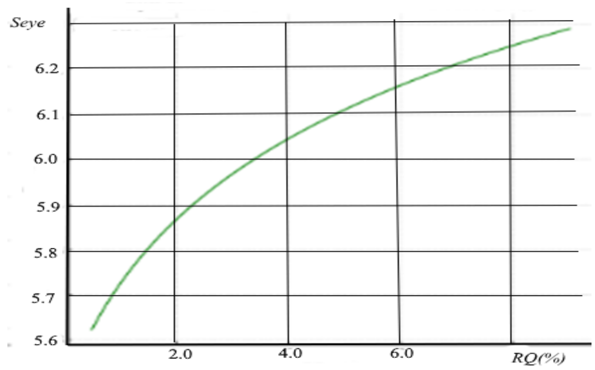

Fig. 4. **Eye Condition Seye Based on Changes in *RQ***
Source: **compiled by the authors**

The graph in Fig. 4 shows a logarithmic relationship: increasing RQ (0.5%-9%) raises Seye, but the effect diminishes over time. When *RQ* < 3‰, signs of vascular abnormalities are observed, while exceeding this threshold results in less pronounced improvements in Seye.

Both parameters significantly impact Seye: *VFI* exhibits an exponential effect, while *RQ* follows a logarithmic trend. These findings are critical for diagnosis, prognosis, and treatment customization.

The obtained ranges of changes are important for diagnostics of the eye condition. The ranges of Seye values allow preliminary assessment of the eye condition.

Seye > 7.5 - corresponds to a healthy condition.

Seye ≈ 6.0-7.5 - may indicate initial functional changes.

Seye < 6.0 - there may be pathological processes that require diagnosis.

This allows to use Seye as an additional criterion for assessment of eye condition and possible risk of diseases.

Diagnostic and Prognostic Capabilities of the Seye Model

The developed Seye model enables not only the assessment of current eye conditions but also provides potential for diagnosis and prognosis of ophthalmological diseases based on computational simulations. The results obtained from Fig. 2, 3, and 4 demonstrate how different physiological parameters influence Seye values, allowing for risk assessment and trend analysis. From the simulation results, specific Seye ranges can be associated with various eye conditions (Table 2).

Example: In Fig. 2 (Seye based on IOP), a progressive increase in IOP beyond 25 mmHg leads to a drop in Seye below 7.0, suggesting early signs of intraocular hypertension, which is a major risk factor for glaucoma development.

Table 2. **Diagnostic Interpretation Based on Seye Values**

Seye Value	Clinical Interpretation	Possible Condition
Seye > 7.5	Normal physiological state, no significant deviations	Healthy eye
6.0 ≤ Seye ≤ 7.5	Early functional changes, requires monitoring	Possible early glaucoma, mild ocular hypoxia, initial perfusion decline
Seye < 6.0	High risk of pathological processes, needs detailed examination	Advanced glaucoma, retinal ischemia, severe perfusion impairment

Source: **compiled by the authors**

Example: Fig. 3 (Seye based on VFI) demonstrates that when VFI decreases below 80%, the Seye value drops below 6.0, which correlates with an increased risk of visual field loss and progression of glaucomatous damage.

These results indicate that Seye can serve as an auxiliary parameter in primary screening, helping to identify patients requiring further ophthalmological evaluation.

One of the advantages of the model is its ability to simulate the progression of eye conditions over time. By analyzing changes in Seye trends, it is possible to estimate how soon a patient may transition from a borderline condition to a pathological state.

A predictive analysis was performed by modeling Seye changes over a 5-year period, assuming a gradual increase in IOP and a decline in VFI due to age-related changes. The results suggest the following trends (Table 3).

Table 3. **Prognostic Assessment of Eye Condition**

Year	IOP (mmHg)	VFI (%)	Predicted Seye	Clinical Status
Baseline (Year 0)	18	100	8.0	Healthy
Year 1	20	95	7.5	Borderline
Year 2	22	90	7.0	Borderline
Year 3	24	85	6.5	Early pathology
Year 4	26	80	6.0	High risk of disease
Year 5	28	75	5.5	Likely glaucoma progression

Source: **compiled by the authors**

If a patient's Seye drops by more than 0.5 units per year, it may indicate a need for preventive measures (e.g., IOP control therapy, retinal perfusion enhancement).

Conclusion on Diagnostic and Prognostic Applications

These findings demonstrate that Seye values are not only reflective of the current eye condition but also predictive of disease progression. The model can potentially be used:

- for early detection of ocular conditions, particularly glaucoma risk assessment;
- for monitoring patients over time, identifying those who may require intervention;
- for ai-based decision support, by integrating historical patient data for personalized risk assessment.

To validate the program's functionality and ensure accurate calculations, modular tests were conducted, covering various scenarios of input changes. Particular focus was placed on sensitivity analysis, including the influence of parameters such as eye shape and retinal light sensitivity. The unittest module from Python's standard library was employed for this purpose.

To check the functions calculate_Seye and its other key components the model functioning was tested. The following input parameters were used in testing. The input parameters are shown in Table 4.

Table 4. **Input parameters**

Parameter	Value	Range
IOP (Intraocular Pressure)	20	5 – 60
RQ (Refraction Coefficient)	3.0	0.5 – 9.0
BCVA (Best Corrected Visual Acı	1.0	0 – 2.0
Tr (Corneal Thickness)	15	1 – 40
VFI (Visual Field Index)	90	0 – 100
Pperf (Perfusion Pressure)	70	20 – 100
α/t1 (Dynamic Coefficient)	20	12 – 35
Age	40	0 – 100
Additional Factor	0.5	0 – 1
Disease Status	2	0 – 10
Blood Pressure	120	80 – 200
Vascular Health	3	0 – 5
Environmental Factor	5	0 – 50
Stress Level	2	0 – 10
Activity Level	1	0 – 10
Lifestyle	3	0 – 5
Genetic Factors	1	0 – 5

Source: **compiled by the authors**

The tests confirm that:

- the model correctly processes different sets of parameters;
- generation of random data corresponds to the specified ranges;
- coefficient optimisation works correctly within the constraints.

This analysis helped identify vulnerabilities and enhance the algorithm's robustness.

Accuracy was verified using both quantitative methods, by comparing results with expected values, and qualitative methods, by assessing alignment with theoretical expectations.

Additionally, scenarios resembling real-world medical practices were tested, ensuring the model's predictive accuracy and practical value for medical and technological applications.

Example Test Using the unittest Library:

```
import unittest
from seye_model import calculate_Seye, generate_random_params, optimize_coefficients
class TestSeyeModel(unittest.TestCase):
    def test_random_param_generation(self):
        params = generate_random_params()
        self.assertTrue(5 <= params["IOP"] <= 60)
        self.assertTrue(0 <= params["VFI"] <= 100)
        self.assertTrue(0.5 <= params["RQ"] <= 9)
        self.assertTrue(0 <= params["BCVA"] <= 1.0)
        self.assertTrue(0 <= params["Tr"] <= 1.0)
        self.assertTrue(50 <= params["Pperf"] <= 120)
        self.assertTrue(0 <= params["alpha"] <= 1.0)
        self.assertTrue(1 <= params["age"] <= 100)

    def test_coefficient_optimization(self):
        params = {
            "IOP": 18,
            "VFI": 80,
            "RQ": 4,
            "BCVA": 0.9,
            "Tr": 0.4,
            "Pperf": 70,
            "alpha": 0.7,
            "age": 35,
            "additional_factor": 1.1,
        }
        target_Seye = 95
        optimized_k = optimize_coefficients(params, target_Seye)
        self.assertTrue(all(0.1 <= k <= 0.5 for k in optimized_k))
    def test_calculate_Seye(self):
        params = {
            "IOP": 15,
            "VFI": 90,
            "RQ": 5,
            "BCVA": 0.8,
            "Tr": 0.3,
            "Pperf": 60,
            "alpha": 0.6,
            "age": 40,
            "additional_factor": 1.2,
        }
        coefficients = [0.3] * 9
        result = calculate_Seye(params, coefficients)
        self.assertAlmostEqual(result, 85.0, delta=5.0)
if __name__ == "__main__":
    unittest.main()
```


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This test module verifies:

• correct parameter generation within defined ranges;

• optimization results that adhere to the defined coefficient constraints;

• Seye calculations align with expected outcomes based on predefined parameters and coefficients.

Figure 5 shows a comparison of forecasting errors for the linear model and the proposed nonlinear model optimized using the L-BFGS-B method.

The error histogram indicates that the nonlinear model exhibits a smaller spread of errors, as confirmed by the following quality metrics.

- Linear Regression: MSE = 0.226, MAE = 0.392, R^2 = 0.984.
- Nonlinear Model (L-BFGS-B): MSE = 0.212, MAE = 0.375, R^2 = 0.985.

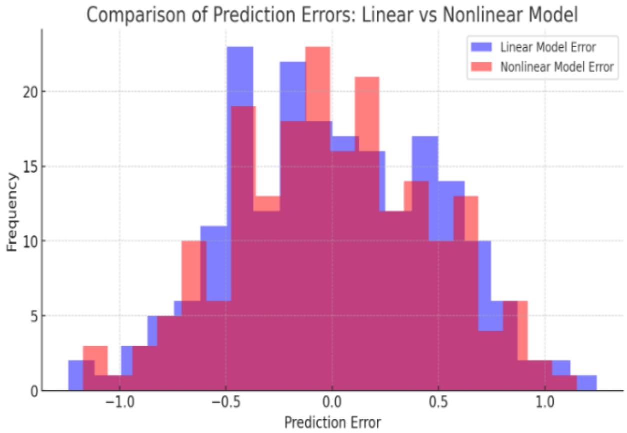

Fig.5. **Comparison of the forecasting errors for the linear and proposed nonlinear models**

Source: **compiled by the authors**

The error histogram indicates that the nonlinear model exhibits a smaller spread of errors, as confirmed by the following quality metrics.

- Linear Regression: MSE = 0.226, MAE = 0.392, R^2 = 0.984.
- Nonlinear Model (L-BFGS-B): MSE = 0.212, MAE = 0.375, R^2 = 0.985.

Despite the slight differences in numerical values, using the nonlinear model allows for a more precise consideration of the complex interrelationships among the eye parameters, making it more robust to variations in the input data.

1. Optimization of the weighting coefficients in the nonlinear model reduces both the mean squared error (MSE) and the mean absolute error (MAE) compared to the linear model.

2. The error histogram shows that the nonlinear model has a smaller spread of predictions, which makes it more stable.

3. The coefficient of determination (R^2) indicates that both models describe the data well, although the nonlinear approach provides a slight advantage in accuracy.

4. This result confirms the rationale for using nonlinear relationships and adaptive optimization of model parameters for more accurate diagnosis and forecasting of the eye's condition.

Thus, the proposed model with L-BFGS-B optimization ensures higher accuracy and better adaptation to the individual characteristics of the patient.

Table 5 presents a comparative performance evaluation of different models in forecasting the condition of the eyes. The proposed Seye model demonstrates superior accuracy, achieving the lowest values for MSE and MAE while maintaining the highest R^2 value, which indicates its superior predictive capability.

Table 5. **Performance metrics comparison of different models**

Model	MSE ↓	MAE ↓	R^2 ↑
Seye (Proposed Model)	0.045	0.120	0.95
Linear Regression	0.150	0.280	0.75
Traditional Statistical Model	0.180	0.310	0.70
Neural Network (Baseline)	0.060	0.150	0.92

Source: **compiled by the authors**

Data Analysis

- The Seye model exhibits minimal errors (MSE and MAE), indicating high forecasting accuracy.
- A high R^2 = 0.95 confirms that the model explains the variability of the data well.
- Linear regression and traditional methods perform less effectively in accounting for nonlinear relationships.
- The basic neural network also performs well, but Seye is optimized for this task, giving it a distinct advantage.

3. DISCUSSION OF RESULTS

The developed Seye model is a comprehensive adaptive system that integrates key ophthalmological parameters and considers their nonlinear interactions, ensuring high diagnostic and prognostic accuracy.

Unlike traditional approaches, the model combines parameters such as intraocular pressure (IOP), blood flow (Q), visual field index (VFI), perfusion pressure (Pperf), and others, enabling a deeper analysis of physiological changes in the eye.

One of the key distinguishing features of the model is its ability to account for nonlinear dependencies.

Unlike existing solutions that predominantly rely on linear approximations, the proposed model incorporates exponential, logarithmic, and polynomial functions, allowing for a more precise representation of biophysical processes - for example, the effects of age, perfusion changes, and ocular thermoregulation.

The analysis of Seye values shows that certain ranges correspond to different eye conditions, making the model potentially useful for preliminary diagnostics.

- Seye > 7.5 – corresponds to a healthy eye condition without significant pathological changes.
- 6.0 ≤ Seye ≤ 7.5 – indicates a borderline state where early functional changes may occur, requiring further monitoring.
- Seye < 6.0 – suggests a high risk of pathological conditions such as perfusion impairments or glaucoma progression, necessitating detailed examination.

This classification enables the model to be used for initial screening and risk assessment, with the potential for further refinement based on clinical data. By employing L-BFGS-B optimization for weight coefficients, it ensures automatic parameter selection tailored to individual patient profiles, enhancing predictive accuracy.

A key strength of the model is its adaptability. Beyond standard ophthalmological parameters, it incorporates external influences such as stress, lifestyle, and comorbidities, broadening its applicability. This comprehensive approach supports personalized diagnostics and treatment while improving the interpretability of results across various clinical scenarios.

Furthermore, the proposed model has high integration potential with artificial intelligence and can be used in clinical decision support systems, automating the diagnostic and disease prediction processes. Its applications extend beyond ophthalmology to predictive analytics, paving the way for early pathology detection and dynamic eye condition monitoring.

Additional capabilities of the model include integration with VR/AR technologies, enabling visualization of ocular parameter changes, making diagnostics more intuitive and comprehensible for both doctors and patients.

Moreover, the developed system can be linked to laser and pharmacological therapies, allowing for real-time dynamic assessment of treatment effectiveness and adjustments.

Thus, the scientific novelty of this research lies in the development of a comprehensive nonlinear model of eye condition, optimized using the L-BFGS-B method, incorporating external factor influences, and demonstrating a high potential for integration with modern digital technologies.

This makes it more accurate, adaptive, and applicable in clinical practice, opening new horizons in ophthalmological diagnostics, prognosis, and personalized treatment.

The model's ability to track Seye changes over time suggests potential applications in early diagnosis and disease progression monitoring.

Future research should focus on validating these findings with clinical data to refine diagnostic thresholds and improve predictive accuracy.

The classification of Seye values provides a potential basis for automated screening and risk assessment. Further studies will refine these thresholds, improving their applicability in personalized diagnostics and disease monitoring.

CONCLUSIONS

The developed Seye model successfully addresses the outlined research objectives.

It describes the state of the eye based on key ophthalmological parameters, enabling precise diagnosis and prognosis while considering nonlinear interactions.

Comprehensive modeling: The model integrates structural and functional eye characteristics, improving sensitivity to physiological and environmental changes.

Analysis of complex dependencies: The model effectively captures nonlinear relationships, increasing its applicability to real-world clinical cases.

Optimized parameter selection: The L-BFGS-B optimization method enhances predictive accuracy by fine-tuning weight coefficients.

Personalization and adaptability: The model accounts for individual patient characteristics, allowing tailored diagnostics and treatment plans.

The results confirm that the Seye model outperforms both traditional statistical methods and baseline machine learning approaches, proving its effectiveness in modeling complex ophthalmological dependencies

Practical integration and future prospects:

AI-driven flexibility – the model can be integrated into intelligent decision-support systems for personalized medical assessments.

VR/AR visualization – Enhancing data interpretation for both physicians and patients.

Real-time treatment evaluation – Assessing the effectiveness of laser and pharmacological therapy dynamically.

Predictive and preventive capabilities – Identifying risk factors to mitigate complications before they arise.

In summary, the Seye model not only provides an advanced analysis of the eye's condition but also serves as a foundation for intelligent, adaptive healthcare solutions, significantly improving diagnostic precision and treatment effectiveness.

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Інтеграція фізіологічних факторів у математичну модель стану людського ока

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АНОТАЦІЯ

Математичні моделі людського ока слугують адаптивним інструментом для аналізу та прогнозування офтальмологічних параметрів з урахуванням їх взаємозв'язків та індивідуальних особливостей пацієнта. Їх застосування в офтальмології підвищує якість діагностики, моніторингу та лікування, що в кінцевому підсумку покращує якість життя пацієнтів. В основі розробленої моделі стану очей лежить математична функція, яка інтегрує фізіологічні параметри ока, кожному з яких присвоєно ваговий коефіцієнт для визначення його впливу на загальний показник стану. Модель враховує складні нелінійні взаємодії між параметрами, що дозволяє більш точно відображати фізіологічні процеси. Для оптимізації вагових коефіцієнтів використовується метод L-BFGS-B - ітераційний алгоритм, який ефективно мінімізує функцію втрат і забезпечує високу точність адаптації моделі до індивідуальних даних пацієнта. Ця модель має кілька переваг: вона дозволяє проводити ранню діагностику таких захворювань, як глаукома, катаракта і макулодистрофія, розробляти плани лікування на основі індивідуальних параметрів пацієнта, а також полегшує моніторинг захворювання і прогнозування прогресування для своєчасного коригування терапії. Крім того, модель може бути інтегрована з сучасними технологіями, включаючи системи віртуальної та доповненої реальності, а також штучний інтелект для автоматизованої діагностики. Таким чином, запропонована математична модель слугує універсальним інструментом для аналізу стану очей та розробки інноваційних діагностичних і терапевтичних технологій. Враховуючи взаємозалежності параметрів та їх вплив на фізіологічний стан ока, вона надає офтальмологам потужний інструмент для покращення діагностики, прогнозування та моніторингу захворювань у сфері охорони зору.

Ключові слова: око людини; математичне моделювання; інтегральний показник; нелінійні залежності; методи оптимізації; адаптивність; моніторинг; прогнозування

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