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Original Study

A neural network process for the fractional order lungs cancer operation system

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Abstract

The purpose of current research is to provide the solutions of the fractional lungs cancer operation system using one of the neural network approaches. The mathematical model is divided into immune/epithelial cells, tumor suppressor genetic factor, evolution factor oncogenes, and blood lung cancer vessels. The fractional derivatives are performed more competently as compared to integer order derivatives. A neural network approach based on the Levenberg-Marquardt Backpropagation is applied to solve the fractional kind of derivative to have the solution of the system. Eighteen numbers of neurons along with sigmoid activation function in the hidden layer are used in the neural network process, while the data is created via Adam numerical solver with the selection of different percentages including testing, training and verification. The correctness of the designed neural network scheme is observed through the matching of the outcomes, best training performances and insignificant absolute error. Moreover, some tests based regression, state transition, and error histogram are also been used to check the validity of the proposed scheme.

Keywords: Fractional lungs cancer, mathematical model, levenberg-marquardt backpropagation, neural network, activation function.
AMS 2020 codes: 34A12; 68T07.

1 Introduction

Among the most deadly cancers in the globe, Lung Cancer (LC) still causes a great deal of sickness, death, and financial strain on medical networks. About two million additional instances and over 1.8 million fatalities occurred five years ago independently, which makes it the worlds top source of death due to cancer [1]. LC affects a greater number of individuals annually than breast, prostate, and colorectal cancers taken together, which emphasizes the critical need for improved prevention, initial detection, and treatment strategies. The monetary burden is additionally significant, with yearly worldwide expenses for therapy, lost employment, and hospice care topping one hundred eighty billion dollars [2]. Medical facilities with little funding are particularly affected by this economic strain. In accordance with the American Cancer Society, the illness is divided into two categories: LC based non-small cells, which makes up around 85 percent of cases, and the more dangerous LC based small cells, which is characterized by rapid progression and earliest metastases [3]. Big cell malignancy, squamous cell carcinoma, and adenocarcinoma are molecule-by- different subgroups of the first category, according to the precision health care model, all require specific therapy approaches. Fibroblast cells development dimension receptors amplifiers and other genetic changes are characteristic of

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cancers of squamous cells, whereas enforceable changes like skin growth dimension receptors or kinase based on plastic lymphoma changes are common in a tumor that is usually found in people who do not smoke. Multidisciplinary treatment strategies are necessary since the current studies highlight cancer microenvironment variation, such as vasculature and invasion of immune cells, for the purpose to create a confrontation with conventional medicines [4, 5]. Nicotine is the primary risk factor, with 80–90% of cases linked with regular smoking and passive contact. Gas called radon, asbestos fibers, air pollution, and other occupational and ecological risks constitute additional major concerns. Depending on the location, radon, a hazardous byproduct of soil nuclear deterioration, can enter areas of occurrence and cause anywhere from three percent to fourteen percent of LC cases [6]. Likewise, industrial exposition to mesothelioma remains a concern in industries such as building and mining, having a 20–40 year incubation period based on sensitivity and illness progression. Remarkably, twenty-five percent of LC sufferers are nonsmokers, with East Asian women having the highest incidence, and numbers exceeding fifty percent in positive groups. This propensity encompasses lifestyle variables, interior pollutants, and genetic vulnerability, which cast doubt on the widely held belief that tobacco is the sole cause of LC. The acetylation of proteins and nucleotide dimethyl are two examples of epigenetic modifications that are increasingly being identified as significant factors in cancer-causing genes, opening up new avenues for prevention. With an average recurrence probability of nineteen percent and only five percent for distant sickness, the prospects for survival for LC remains bleak. This is due to the impact of delayed execution at an advanced point and the unclear effectiveness of treatment for incurable cancer [7]. Low-dose computerized tomography monitoring can increase lifespan by identifying cancers at earlier, curable phases. Yet difficulties, inaccurate results, exorbitant expenses, and inadequate screening techniques are impeding widespread adoption. Though its integration into standard medical procedures is still in its early phases, artificial intelligence has shown promise in diagnostic imaging by reducing errors in diagnosis by accurately distinguishing between nodules that are malignant and benign. LC has been controlled, mostly through the development of immunology and focused medicines, which have changed patient care. Initial research revealed a discernible thirty-five percent decrease in progression of disease associated with amalgamation treatments according to nivolumab and ipilimumab immune preservation treatment for battling recurrence following activity. LC requires a great deal of work that involves global tobacco abstinence and collaboration, later-stage precision medication, universal access to tests, and comprehensive prevention [8]. A number of mathematical schemes have been presented to solve the LC model, e.g., Amilo et al. [9] presented the fractional kind of mathematical system for LC by applying the integrated therapeutic scheme, Saeidi, et al. [10] provided an optimal solution based LC by applying the comprehensive Bessel polynomials, Abdullah, et al. [11] presented the mathematical modeling along with the analysis of smoking using the LC dynamics. Ghita et al. [12] provided the LC dynamics based on the fractional kind of impedance modeling using the mimicked setup of lung tumor. Hassani et al. [13] provided the investigations based on the fractional tumor-immune communication system associated to LC through comprehensive Laguerre polynomials. Eftimie et al. [14] provided the mathematical examination of innate immune comebacks based LC. Lee et al. [15] provided the optimal control based on the mathematical cancer therapies system. Kolev et al. [16] discussed the numerical simulations based on the interactions of cellular and tumor immune system using the treatment of LC. All these above-mentioned approaches have their own significances, merits, and demerits, while the solutions of the nonlinear mathematical model based on the LC system has never been exploited before using the neural network procedures.

The purpose of current research investigations is to provide the solutions of the fractional lungs cancer operation system (FLCOS) using the Levenberg-Marquardt Backpropagation (LMBP). Three cases based on fractional order have been taken between 0 and 1 to present the solution of the FLCOS. Whereas, the neural network solver based on the LMBP has never been applied before to solve the FLCOS. Some of the recent applications of neural network are higher order singular nonlinear differential equations [17], and fifth order order singular models [18]. Some of the novel comments of this study are presented as:

- * The mathematical form of the FLCOS is discussed first time based LMBP neural network.
- * The fractional order derivatives of the LC system provide more accurate results of the model.
- * Eighteen numbers of neurons and the log-sigmoid activation function are used in the hidden layer process.
- * The correctness of the model is observed through the overlapping of the solutions, and different test performances.

The rest of the manuscript is organized as: Mathematical form of the FLCOS is shown in Section 2. The LMBP neural network is given in Section 3, and the numerical results of the FLCOS are portrayed in Section 4, while the concluding remarks are listed in Section 5.

2 Mathematical FLCOS model

This section presents the mathematical formulation based on the LC, which has been separated into the cells of immune/ epithelial, tumor suppressor genes, factor oncogenes growth, blood vessels in LC as [9]:

$$\begin{aligned}\frac{dN(\theta)}{d\theta} &= \left(\lambda \left(1 - \frac{N(\theta)}{g} \right) - (\mu P(\theta) + \beta_1 I(\theta)) \right) N(\theta), N_0 = k_1, \\ \frac{dI(\theta)}{d\theta} &= \phi_1 I_0 - (\beta_2 P(\theta) + \phi_3) I(\theta) + \phi_2 (N(\theta))^2, I_0 = k_2, \\ \frac{dP(\theta)}{d\theta} &= (\gamma N(\theta) - \beta_3 I(\theta) - \delta) P(\theta), P_0 = k_3,\end{aligned}\tag{1}$$

where $N(\theta)$ shows the cells of cancer cells of Lung Tissue (LT), $I(\theta)$ is the cancer cells banquet in the whole body, and $P(\theta)$ presents the immune cells in LT. The description of the parameters is given in Table 1.

Table 1 Angular deceleration vs time.

Parameters	Definition
λ	Cell rate of developing cancer
g	Competence of transport
β_1	Immune cells effects
β_3	Transporting cancer cell nutrients and sanctioning metastasis
ϕ_1, ϕ_2, ϕ_3	Growth factor effects
θ	Time
β_2	Association in immunity cells and cancer growing
δ	Remaining parts of the body and spreading of death rate of cancer cells
μ	Spreading rate of the cells of cancer via lungs tissue using the outstanding body organs
γ	Rate of cancer cells based tissue expanding in lungs to remaining parts of bod
k_1, k_2, k_3	Initial conditions (ICs)

The fractional form of the LC model is given as:

$$\begin{aligned}
\frac{dN^\alpha(\theta)}{d\theta^\alpha} &= \left(\lambda \left(1 - \frac{N(\theta)}{g} \right) - (\mu P(\theta) + \beta_1 I(\theta)) \right) N(\theta), N_0 = k_1, \\
\frac{dI^\alpha(\theta)}{d\theta^\alpha} &= \phi_1 I_0 - (\beta_2 P(\theta) + \phi_3) I(\theta) + \phi_2 (N(\theta))^2, I_0 = k_2, \\
\frac{dP^\alpha(\theta)}{d\theta^\alpha} &= (\gamma N(\theta) - \beta_3 I(\theta) - \delta) P(\theta), P_0 = k_3.
\end{aligned} \tag{2}$$

Where α presents the Caputo derivative (CPD), which is a form of fractional order derivative and widely applied in fractional calculus. The values of CPD are taken between 0 and 1, mainly valuable to model the systems having hereditary and memory properties, whereas it captures non-local performance and long-term dependences. In comparison with other derivatives, like Riemann-Liouville, the CPD permits to apply the conventional ICs, which perform more appropriately to solve the real-world applications in different areas like engineering, physics, and finance. The CPD is also extensively implemented to design anomalous viscoelasticity, diffusion, and other intricate sensations.

3 Methodology

This section presents the neural network for the FLCOS using eighteen neurons. The optimization test performances using the LMBP are presented as:

3.1 Neural structure based LMBP

The proposed structure using the LMBP for the FLCOS is provided based a hidden layer structure is provided as:

$$\begin{bmatrix} t_1 \\ t_2 \\ t_3 \\ \vdots \\ t_{18} \end{bmatrix} = \Delta \left(\begin{bmatrix} w_{1,1} \\ w_{1,2} \\ w_{1,3} \\ \vdots \\ w_{1,18} \end{bmatrix} [\theta] + \begin{bmatrix} \beta_{1,1} \\ \beta_{1,2} \\ \beta_{1,3} \\ \vdots \\ \beta_{1,18} \end{bmatrix} \right), \tag{3}$$

and

$$\begin{bmatrix} N(\theta) \\ I(\theta) \\ P(\theta) \end{bmatrix} = \left(\begin{bmatrix} \omega_{1,1} & \omega_{2,1} & \omega_{3,1} & \cdots & \omega_{18,1} \\ \omega_{1,2} & \omega_{2,2} & \omega_{3,2} & \cdots & \omega_{18,2} \\ \omega_{1,3} & \omega_{2,3} & \omega_{3,3} & \cdots & \omega_{18,3} \end{bmatrix} \begin{bmatrix} t_1 \\ t_2 \\ t_3 \\ \vdots \\ t_{18} \end{bmatrix} + \begin{bmatrix} b_{3,1} \\ b_{3,2} \\ b_{3,3} \end{bmatrix} \right), \tag{4}$$

where Δ is the activation sigmoid functions, β and b present the biases, w and ω are the weights, while $N(\theta)$, $I(\theta)$, and $P(\theta)$ are the outcomes.

3.2 Log-sigmoid function

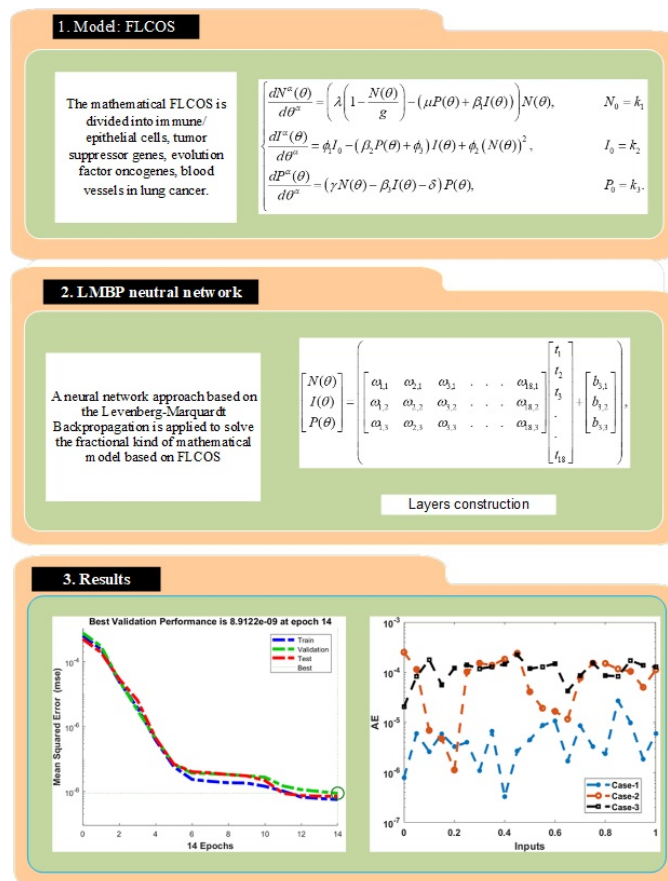
The mathematical log-sigmoid function is implemented to present the performances of real-values in 0 and 1 inputs, which are shown as:

$$\Delta = (1 + e^{-\theta})^{-1}, \tag{5}$$

The aforementioned function curve displays S shape that is primarily used to stimulate in neural networks processes. The mathematical framework can comprehend the complex layouts thanks to this function, which is a nonlinear function. The standard log-sigmoid is measured via intensive computations generally for hardware implementations.

3.3 Procedure performances based LMBP

One technique that is frequently used in minimization strategies for training artificial neural networks is LMBP, which is generally adjusted via the backpropagation approach to associate the Gauss-Newton technique (GNT). LMBP acquaints its step size by implanting the severest descent and GNT that quickly perform convergence in comparison of the predictable backpropagation methods. The extremely complex loss levels generated by deep learning are handled by LMBPs versatility. According to specific investigations, LMBP is well-structured for various networks because it relies on the estimation of Hessian matrix structures, however it is operationally costly for big systems. LMBP has a number of benefits, including the ability to handle poorly trained situations when gradient-based approaches are ineffective. In order to achieve modest minimum local principles, LMBP employs mining and prospecting to acquire dynamic compromises by adding a damping aspect, which prevents instability and premature convergence. Figure 1 shows the mathematical FLCOS, including neural network methodology, and results of the model.



(a)

Fig. 1 Neural network values using LMBP for the FLCOS.

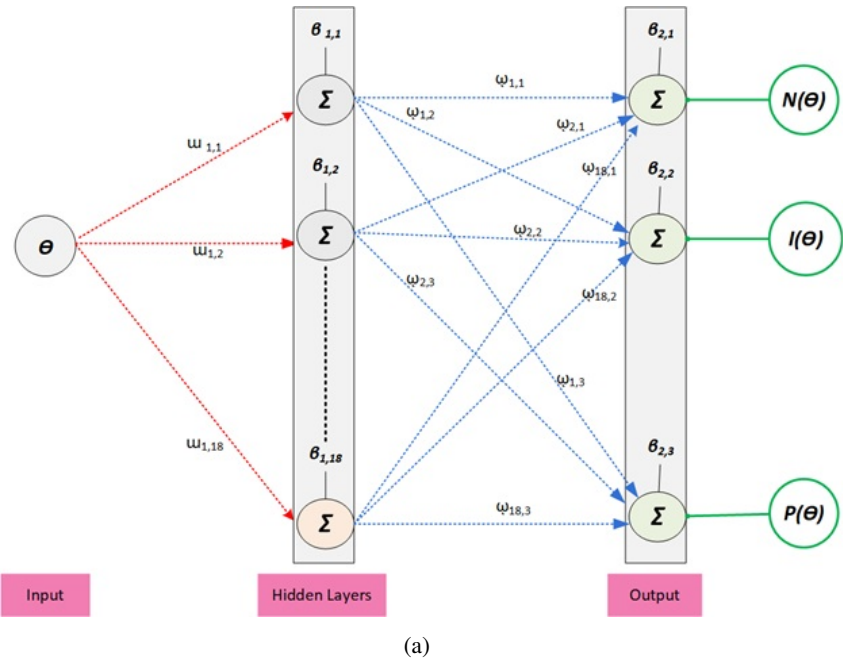


Fig. 2 A single process of neural network for the FLCOS.

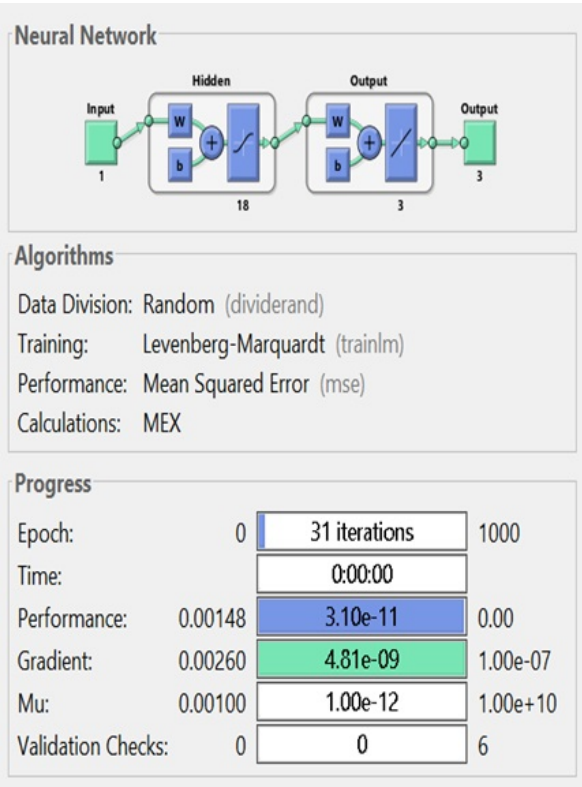


Fig. 3 A design of neural network with the training of LMBP for the FLCOS.

Figure 2 shows the single hidden layer construction, while Figure 3 presents the design of neural network with the training of LMBP for the FLCOS.

4 Results of the LCOM

In this section, the results of the FLCOS have been presented in three different cases of fractional order using the proposed structure.

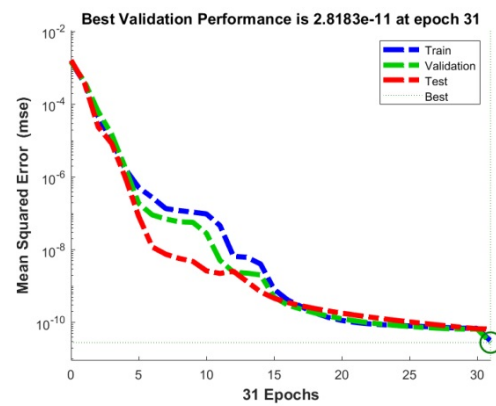
Case 1: Consider the model (1) is updated by taking $\alpha = 0.1$, $\lambda = 0.3$, $g = 10000$, $\mu = 0.01$, $\beta_1 = 0.01$, $\phi_1 = 0.03$, $\beta_2 = 0.01$, $\phi_2 = 0.04$, $\gamma = 0.07$, $\beta_3 = 0.04$, $\delta = 0.001$, $\phi_3 = 0.001$, and the ICs are 0.1, 0.2, and 0.3 as [9]:

Case 2: Consider the model (1) is updated by taking $\alpha = 0.5$, $\lambda = 0.3$, $g = 10000$, $\mu = 0.01$, $\beta_1 = 0.01$, $\phi_1 = 0.03$, $\beta_2 = 0.01$, $\phi_2 = 0.04$, $\gamma = 0.07$, $\beta_3 = 0.04$, $\delta = 0.001$, $\phi_3 = 0.001$, and the ICs are 0.1, 0.2, and 0.3 as [9]:

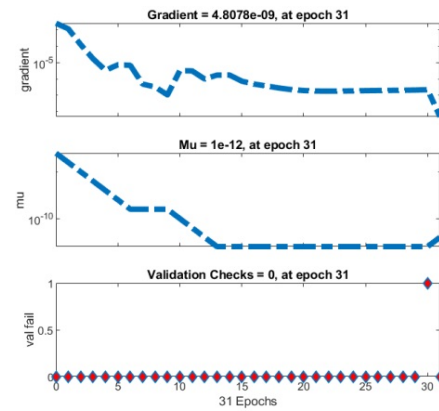
Case 3: Consider the model (1) is updated by taking $\alpha = 0.9$, $\lambda = 0.3$, $g = 10000$, $\mu = 0.01$, $\beta_1 = 0.01$, $\phi_1 = 0.03$, $\beta_2 = 0.01$, $\phi_2 = 0.04$, $\gamma = 0.07$, $\beta_3 = 0.04$, $\delta = 0.001$, $\phi_3 = 0.001$, and the ICs are 0.1, 0.2, and 0.3 as [9]:

Figures (4,5,6,7,8) indicate the numerical FLCOS results using the training performances of LMBP. Figure (4) (a to c) designates the best authentication, while the transition state (Tran. State) is provided in Figure (4) (d to f). The best authentications are provided to reduce the mean square error (MSE) for FLCOS results using the training performances of LMBP at epochs 31, 14 and 7 for 1st to 3rd case of the model, which are reported as 2.81833×10^{-11} , 8.91222×10^{-09} , and 8.50954×10^{-09} . The LMBP method offers optimal verification capabilities using optimal integration, which is often determined by indicators like MSE. The LMBP values are reported via fast convergence to perform the insignificant error, widely applied in small iterations. By minimizing the discrepancy between observed and anticipated results, LMBP effectively optimizes the algorithm's biases and weights, improving its reliability and precision. The performance-oriented ideal verification is primarily accomplished by meticulously altering the hyper parameter settings and carrying out the proper system configuration. The Tran. State values are given in Figure (4) (d to f), which are performed as 4.8078×10^{-09} , 7.2278×10^{-08} , and 2.9779×10^{-08} , whereas the values of Mu are shown as 1×10^{-12} , 1×10^{-11} , and 1×10^{-10} for the mathematical FLCOS. The gradient's measurements indicate the pace of inaccuracy shift depending on the set of parameters that guide the procedure for optimization. Mu introduces a value of normalization, also known as the coefficient of dampening, that is utilized to improve both the direction and through modifying the Gauss-Newton techniques and steepest decline. The gradient's efficiency often decreases as the initial numbers rise, indicating closure. Nonetheless, Mu controls to allow for steady and efficient efficiency, which has been primarily improved as it is not the ideal result. Figure (5) (a to c) describes the fitting curve for the FLCOS results using the training performances of LMBP. The fitness function (Fit. Funct) measures for output elements is normally achieved via various metrics. By optimizing the network's parameters and weights, the technique lowers mistakes and improves the predicted results fit to actual information. The Fit. Funct strong results demonstrate the framework's basic architecture for effectively obtaining information. The values based on the error histogram (Err. Hist) are illustrated in Figure (4) (d to f), which are 2.46×10^{-08} , 9.92×10^{-07} and 1.49×10^{-05} for the FLCOS results using the training performances of LMBP. The error dispersion in real and anticipated results throughout the testing, authentication, and training phases of data is displayed by Err. Hist in LMBP using 20 bins, highlighting the efficiency of the framework. Figs. 6 to 8 present the regression illustrations the FLCOS results using the training performances of LMBP. These regression depictions indicate fast process via input ranks connecting for the objective topics. Table 2 indicates the FLCOS results using the

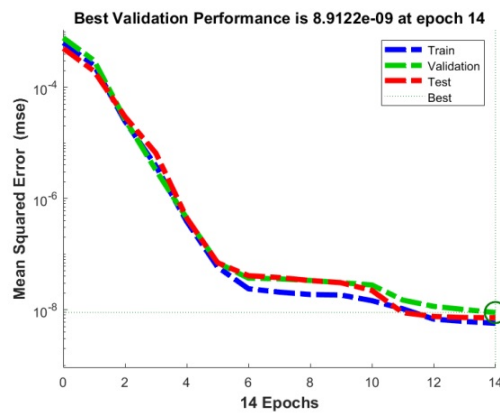
training performances of LMBP.



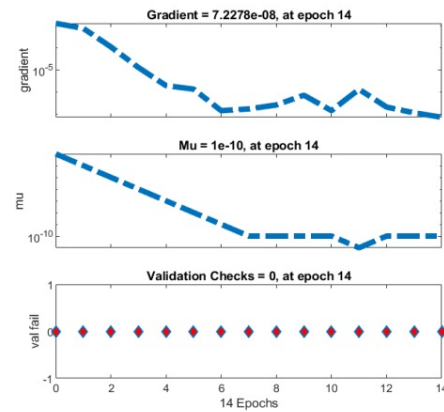
(a) Best validation performances (1)



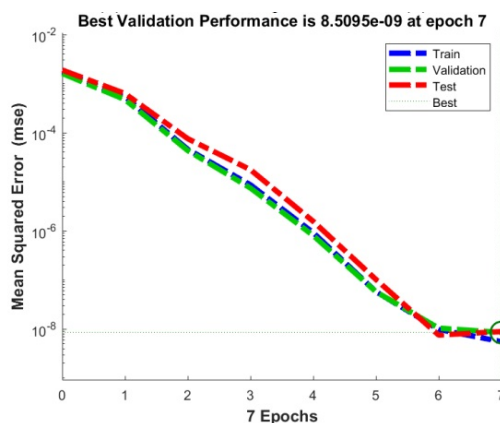
(b) Tran. State (1)



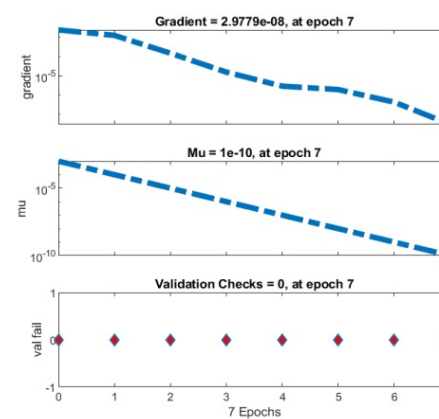
(c) Best validation performances (2)



(d) Tran. State (2)

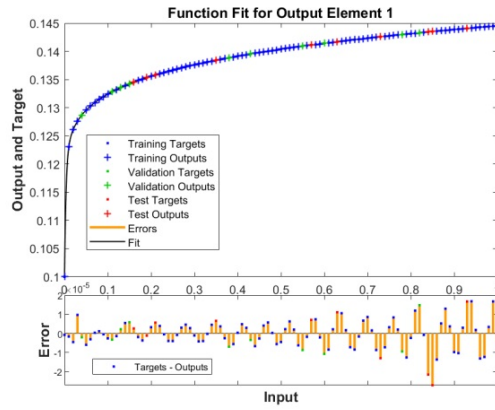


(e) Best validation performances (3)

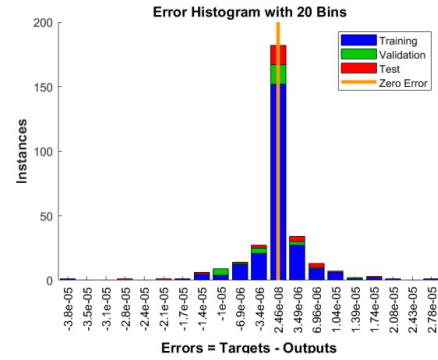


(f) Tran. State (3)

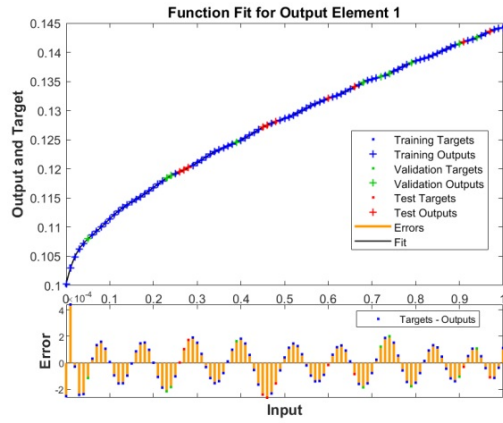
Fig. 4 Optimal training values and Trans. State for the FLCOS.



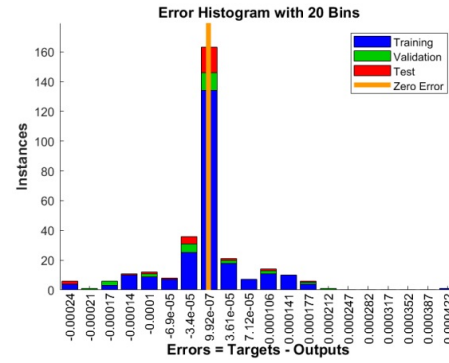
(a) Fit Funct (1)



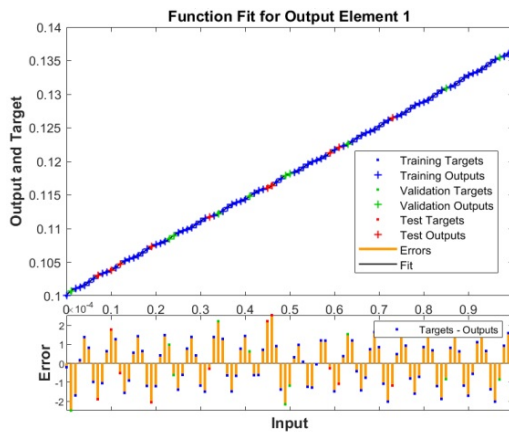
(b) Err. Hist (1)



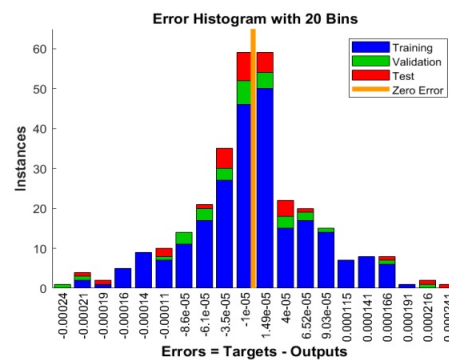
(c) Fit Funct (2)



(d) Err. Hist (2)



(e) Fit Funct (3)



(f) Err. Hist (3)

Fig. 5 Optimal training values and Trans. State for the FLCOS.

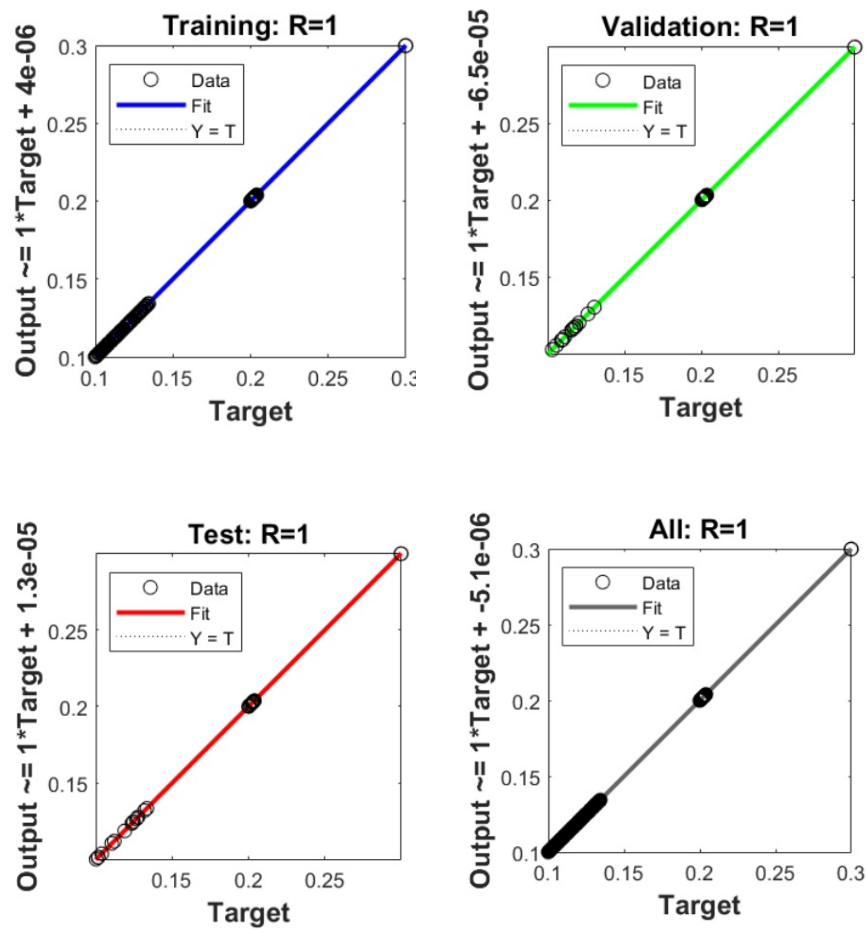


Fig. 6 Regression values for case (1) of FLCOS.

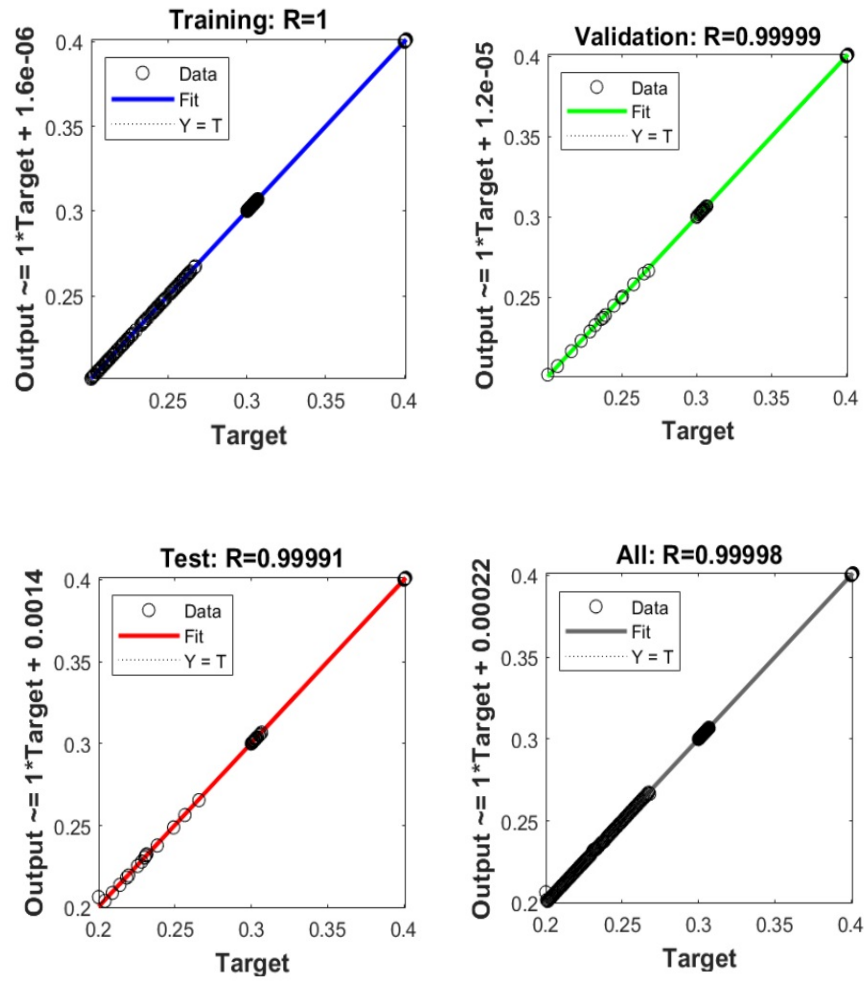


Fig. 7 Regression values for case (2) of FLCOS.

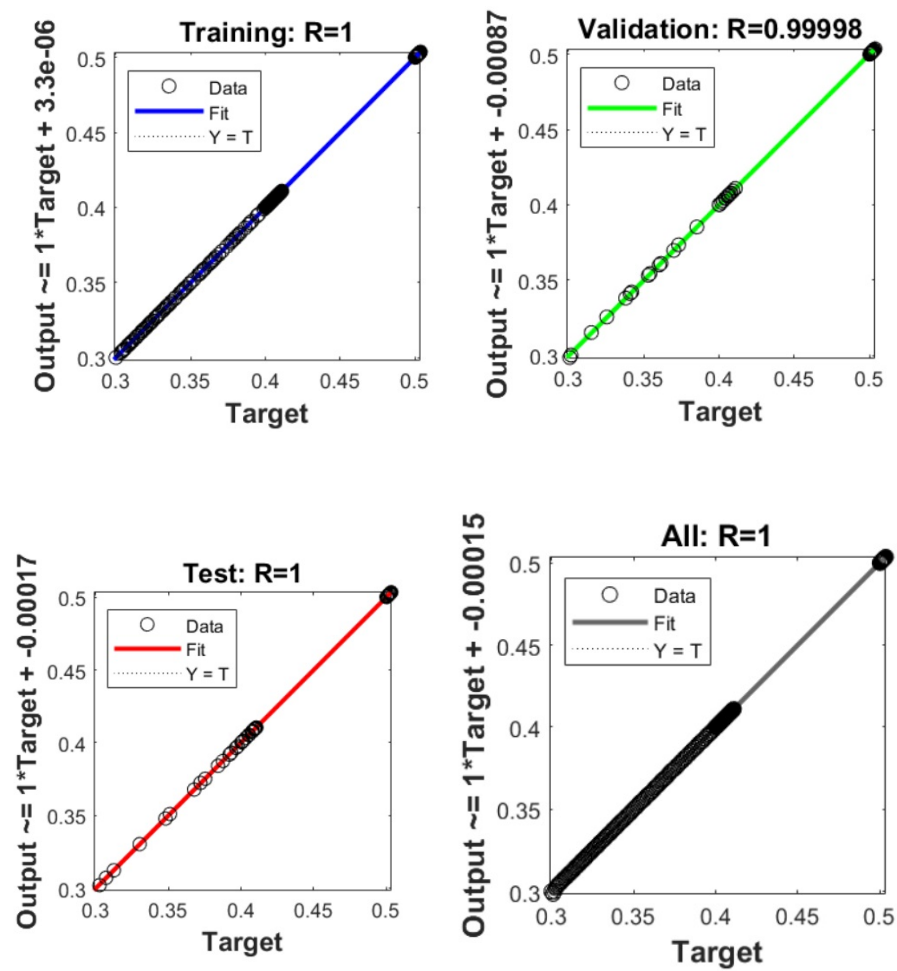
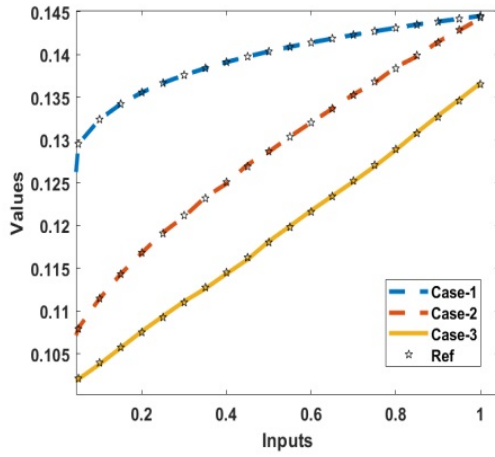
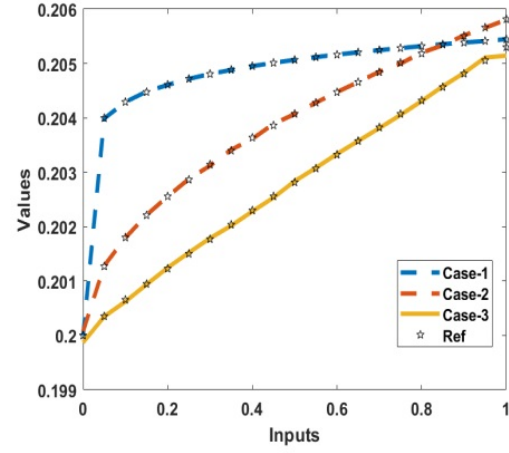
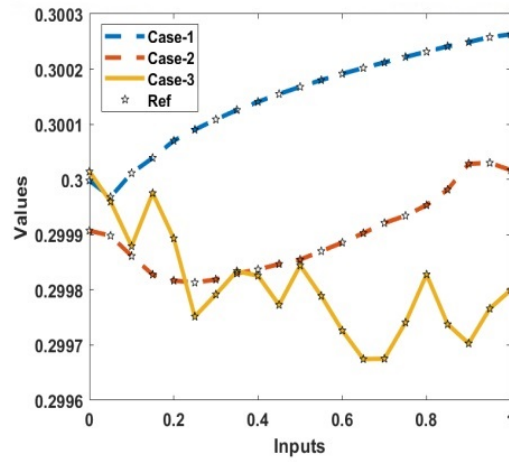


Fig. 8 Regression values for case (3) of FLCOS.

(a) Result performances: $N(\theta)$ (b) Result performances: $I(\theta)$ (c) Result performances: $P(\theta)$ **Fig. 9** Output values for the FLCOS using the training of LMBP.

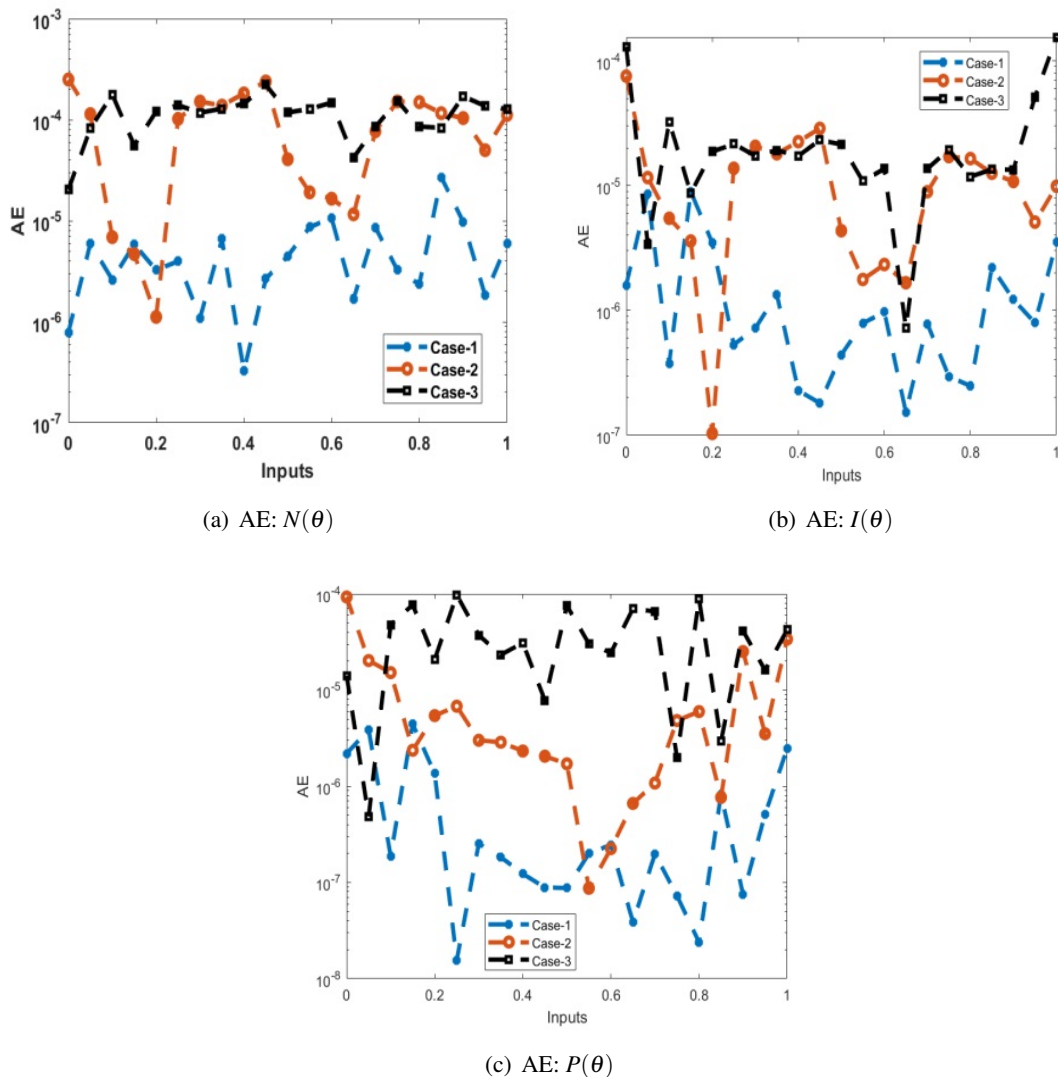


Fig. 10 Output values for the FLCOS using the training of LMBP.

Figure 9 presents the numerical results of the FLCOS using the design of LMBP neural network, which shows that the overlapping of the results is performed for each FLCOS case. These matching indicates the correctness of the proposed solver. Figure 10 presents the AE values for each case of the model, which shows that most of the values are performed around 10^{-04} to 10^{-06} for each case of the FLCOS. These insignificant AE enhances the worth of the proposed scheme.

Table 2 Training procedure for the FLCOS using the LMBP.

Case	MSE(Train)	MSE(Validation)	MSE(Testing)	Performance	Gradient	Mu	Iteration	Complexity
1	3.10307×10^{-11}	2.81833×10^{-11}	6.62677×10^{-11}	3.10×10^{-11}	4.81×10^{-09}	1.00×10^{-12}	31	1 sec
2	5.70217×10^{-09}	8.91222×10^{-09}	7.17650×10^{-09}	5.70×10^{-09}	7.23×10^{-08}	1.00×10^{-11}	14	1 sec
3	5.54041×10^{-09}	8.50954×10^{-09}	8.88814×10^{-09}	5.54×10^{-09}	2.98×10^{-08}	1.00×10^{-10}	07	1 sec

5 Conclusion

The current research provides the solutions of the fractional lungs cancer operation system using neural network. The model is divided into immune/epithelial cells, tumor suppressor genes, evolution factor oncogenes, blood lung cancer vessels. Some conclusions of this study are presented as:

- * The fractional lungs cancer operation system using the neural network has been successfully solved.
- * The fractional derivatives have been provided more competent solutions of the FLCOS.
- * A neural network approach based on the LMBP has been applied to solve the FLCOS.
- * Eighteen numbers of neurons along with sigmoid activation function in the hidden layer have been implemented in the neural network process.
- * The creation of the data has been performed through Adam numerical solver with the selection of different percentages including testing, training and verification.
- * The correctness of the designed neural network scheme has been observed through the matching of the outcomes, best training performances and insignificant AE.
- * Some tests based regression, state transition, and error histogram have also been used to authenticate the validity of the proposed scheme.

The designed LMBP neural network structure can be implemented to solve various problems like singular models, cancer systems, food chain systems, Zika virus models, COVID-19 systems and various types of fluid problems.

6 Declarations

6.1 Conflict of interest:

Not applicable.

6.2 Funding:

Not applicable.

6.3 Author's contribution:

G.C.A.-Validation, Investigation, Formal Analysis, Writing-Original Draft, Conceptualization, Writing-Review & Editing. Finally, author read and approved the final manuscript.

6.4 Acknowledgement:

Not applicable.

6.5 Data availability statement:

All data that support the findings of this study are included within the article.

6.6 Usage of AI tools:

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

References

- [1] Benatar S.R., The coming catastrophe in international health: An analogy with lung cancer, *International Journal: Canada's Journal of Global Policy Analysis*, 56(4), 611–631, 2001.
- [2] Thandra K.C., Barsouk A., Saginala K., Aluru J.S., Barsouk A., Epidemiology of lung cancer, *Contemporary Oncology/Współczesna Onkologia*, 25(1), 45–52, 2021.
- [3] Tang W.F., et al., Timing and origins of local and distant metastases in lung cancer, *Journal of Thoracic Oncology*, 16(7), 1136–1148, 2021.
- [4] Bertolaccini L., Casiraghi M., Uslenghi C., Maiorca S., Spaggiari L., Recent advances in lung cancer research: unravelling the future of treatment, *Updates in Surgery*, 76(6), 2129–2140, 2024.
- [5] Lim J.U., Lee E., Lee S.Y., Cho H.J., Ahn D.H., Hwang Y., Choi J.Y., Yeo C.D., Park C.K., Kim S.J., Current literature review on the tumor immune micro-environment, its heterogeneity and future perspectives in treatment of advanced non-small cell lung cancer, *Translational Lung Cancer Research*, 12(4), 857–876, 2023.
- [6] Oyero O.P., Radiological impact assessment of geogenic radon and radionuclide concentrations on residents of selected regions of Kwara state Nigeria, (PhD Thesis), Kwara State University, Nigeria, 2022.
- [7] Berdel W.E., Unintended regulatory caused early death—A difficult endpoint in cancer patient care and treatment, *Cancers*, 13(6), 1457, 2021.
- [8] MacRosty C.R., Rivera M.P., *Lung Cancer: A Comprehensive Guide for the Clinician*, Humana Press, USA, 2023.
- [9] Amilo D., Kaymakamzade B., Hincal E., A fractional-order mathematical model for lung cancer incorporating integrated therapeutic approaches, *Scientific Reports*, 13(1), 12426, 2023.
- [10] Saeidi H., Hassani H., Dahaghin M.S., Mehrabi S., An optimal solution of lung cancer mathematical model using generalized Bessel polynomials, *Physica Scripta*, 99(12), 125269, 2024.
- [11] Abdullah D.M., Ahmed N.S., A review of most recent lung cancer detection techniques using machine learning, *International Journal of Science and Business*, 5(3), 159–173, 2021.
- [12] Ghita M., Modelling of lung tumor volume growth and respiratory mechanics in lung cancer patients, (PhD Thesis), Ghent University, Belgium 2023.
- [13] Hassani H., Avazzadeh Z., Agarwal P., Mehrabi S., Ebadi M.J., Dahaghin M.S., Naraghirad E., A study on fractional tumor-immune interaction model related to lung cancer via generalized Laguerre polynomials, *BMC Medical Research Methodology*, 23(1), 189, 2023.
- [14] Eftimie R., Barelle C., Mathematical investigation of innate immune responses to lung cancer: The role of macrophages with mixed phenotypes, *Journal of Theoretical Biology*, 524, 110739, 2021.
- [15] Lee D., Oh S., Lawler S., Kim Y., Bistable dynamics of TAN-NK cells in tumor growth and control of radiotherapy-induced neutropenia in lung cancer treatment, *Mathematical Biosciences and Engineering*, 22(4), 744–809, 2025.
- [16] Aksu E., Kayali A., Spasova V., Koleva L., Kolev A., Shumarova S., Primary ectopic breast cancer of the vulva: a case report with a short literature review, *Chirurgia*, 37(1), 45–47, 2024.
- [17] Sabir Z., Wahab H.A., Javeed S., Baskonus H.M., An efficient stochastic numerical computing framework for the nonlinear higher order singular models, *Fractal and Fractional*, 5(4), 176, 2021.
- [18] Sabir Z., Ali M.R., Fathurrochman I., Raja M.A.Z., Sadat R., Baleanu D., Dynamics of multi-point singular fifth-order Lane–Emden system with neuro-evolution heuristics, *Evolving Systems*, 13(6), 795–806, 2022.