

Specific Features Of Developing A Predictive Model For Cancer Probability

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Abstract—Cancer remains one of the most lethal diseases worldwide, which makes its early detection a critical public health priority. The development of early diagnostic systems enables timely identification of individuals with a high risk of developing cancer and supports informed clinical decision-making.

In this study, existing approaches to early cancer diagnosis were systematically analyzed. Neural networks were selected as the methodological foundation for designing the expert system. A knowledge base for the expert system was constructed using domain expertise provided by oncology specialists. Key predictors for building a neural-network model were identified. A mathematical model of the system was implemented in the MATLAB environment using three training algorithms: the Levenberg–Marquardt algorithm, Bayesian regularization, and the conjugate-gradient method.

A structural design of an expert-system-based early cancer diagnostic system is proposed. Future research will focus on developing a deep-learning model to achieve higher accuracy in forecasting cancer probability.

Keywords— intelligent systems; expert system; early cancer diagnosis; neural network; prediction.

I. INTRODUCTION

Early cancer detection remains a key determinant of treatment effectiveness and patient survival outcomes. Despite substantial advancements in cancer therapy, timely identification of malignant tumors enables the use of less invasive treatment strategies, reduces the risk of metastasis, and significantly increases the likelihood of full recovery. However, at the global level, many cancer cases continue to be diagnosed at advanced stages due to the asymptomatic course of several tumor types, insufficient availability of screening programs, and low public awareness regarding risk factors and early signs of the disease.

In recent years, progress in molecular biology, bioinformatics, and medical imaging has led to the emergence of new approaches for early cancer detection. The introduction of high-sensitivity screening tests, analysis of circulating tumor DNA, the use of artificial intelligence for medical image interpretation, and personalized

surveillance programs form the foundation of modern strategies for early diagnostic intervention.

This article examines the key contemporary methods for early cancer detection, their clinical relevance, limitations, and prospects for further development, emphasizing the importance of an integrated approach to reducing cancer-related mortality.

II. METHODS AND MODELS

This study employed methods of analysis and synthesis, computer modeling, and predictive modeling. Existing approaches to the development of expert systems for early cancer diagnosis were systematically examined.

Oncological diseases continue to rank among the leading causes of mortality worldwide, primarily due to the late detection of malignant tumors. Despite advances in imaging techniques, the development of molecular diagnostic approaches, the expansion of screening programs, and the integration of digital technologies into clinical practice, a significant proportion of cancers remain undiagnosed at early stages. This delay directly reduces treatment effectiveness, increases healthcare system costs, and shortens patient survival.

In the context of the rapidly growing volume and complexity of medical data—including imaging studies, laboratory results, biomarkers, and genetic profiles—the need for automated diagnostic data analysis becomes particularly evident. Expert systems, machine learning (ML), deep learning (DL), and modern multi-cancer early detection (MCED) technologies increasingly play a crucial role in this process. These methods enhance diagnostic accuracy, provide standardized data interpretation, minimize human error, and accelerate clinical decision-making.

Relevance of the Study

The relevance of the topic is determined by several critical factors:

- High proportion of late-stage cancer diagnoses. Most malignant tumors are still identified at stages III–IV, which dramatically worsens treatment outcomes and reduces survival rates.

- Diagnostic variability and the human factor. Interpretation of medical images and clinical data largely depends on the specialist's experience, workload conditions, and the quality of diagnostic materials, leading to inconsistent results.

- Rapid growth of medical data volumes. Modern imaging modalities generate thousands of images per patient, creating an objective need for automated and intelligent data-processing tools.

- Advances in artificial intelligence technologies. ML and DL models have already reached expert-level performance in medical image analysis, enabling more accurate and standardized diagnostics.

- Emergence of multimodal and multi-cancer early detection (MCED) systems. MCED technologies based on DNA methylation, fragmentation, and other molecular signatures offer the possibility of detecting dozens of cancer types at early stages using a single blood test.

- Taken together, these factors underscore the high demand for research on modern expert systems and intelligent technologies for early cancer detection.

Objectives of This Study

The objectives of the present research include:

- systematizing the evolution of expert systems, from rule-based models to modern hybrid intelligent approaches;

- examining the application of fuzzy logic and soft-set methods;
- analyzing the role of machine learning and deep neural networks in early oncological diagnostics;
- reviewing expert systems developed for detecting specific cancer types (breast, lung, skin);
- identifying the prospects of emerging MCED technologies.

Table 1. Evolution of Expert Systems in Early Cancer Diagnostics

Period	Methods	Key Characteristics
1980–1990s	Rule-based systems, logical inference	Transparency; limited adaptability
1990–2005	Fuzzy logic, fuzzy rule systems, soft-set theory	Ability to handle uncertainty in clinical data
2005–2015	Machine Learning (SVM, kNN, Decision Trees, Random Forest)	Automated feature extraction and improved classification accuracy
2015–present	Deep Learning (CNN, RNN, Transformers)	High diagnostic accuracy; need for explainability (XAI)
2020–present	Multimodal and MCED (Multi-Cancer Early Detection) systems	Integration of genomics, liquid biopsy, and medical imaging

1. Rule-based and Early Expert Systems

The earliest digital solutions in oncological diagnostics were based on production rules and logical inference models. A classical example is the system developed by Morio S. (1989) [1], implemented in PROLOG for the early detection of breast cancer. Despite its simplicity, this work represented an important milestone in the formation of the concept of automated medical diagnostics.

Later, the emergence of web-based expert systems significantly improved the accessibility of oncological advisory tools [2].

2. Fuzzy Logic and Soft-Set Models

Fuzzy-logic-based methods became the next essential stage in the development of intelligent diagnostic systems, as they allow formalizing the uncertainty inherently present in clinical data.

Recent studies demonstrate that:

- fuzzy neural networks achieve high diagnostic accuracy, which is supported by the findings of Algehyne et al., where model accuracy reaches 98–99% depending on the feature set [3];
- fuzzy-rule systems provide interpretability and robustness of diagnostic decisions [4];
- soft-set models are effectively applied for risk assessment and decision-making in settings with incomplete medical data [5];
- in the study by Ali et al. (2023) the method employed is not a “fuzzy-hybrid”, but rather a meta-learning ensemble combined with CNNs. Therefore, the correct interpretation is that ensemble-based and meta-learning approaches demonstrate high robustness and accuracy in medical image analysis [6].

Collectively, these findings highlight the importance of applying fuzzy logic and hybrid intelligent approaches under conditions of clinical uncertainty.

3. Machine Learning and Deep Neural Networks

3.1. Breast Cancer

Machine learning (ML) and deep learning (DL) have become the foundation of most modern computer-aided diagnosis (CAD) systems.

Recent studies demonstrate the following trends:

- Hybrid models combining convolutional neural networks (CNN) with support vector machines (SVM) provide higher classification accuracy compared with single-architecture approaches. For example, in the study by Guizani et al. (2023), a CNN–SVM hybrid trained on breast ultrasound images demonstrated improved diagnostic accuracy relative to a standalone CNN. Similar findings were reported by S. S. K. (2025), where a CNN + SVM hybrid model achieved an overall accuracy of approximately 91–92%, surpassing the performance of most conventional CNN-based classifiers [7, 8].

- Transfer learning significantly enhances the accuracy of mammography classification, with Aljuaid et al. demonstrating performance improvements reaching state-of-the-art levels [9].

- CNN-based models are successfully applied to the analysis of thermographic and infrared imaging, improving the detection of abnormal heat patterns associated with malignancy [10].

- ML classifiers exhibit robustness to heterogeneous datasets and are increasingly used for triage assessment and automation of diagnostic workflows [11].

3.2. Lung Cancer

Machine learning models applied to low-dose computed tomography (LDCT) achieve high AUC and F1-scores, making them suitable for the early detection of pulmonary nodules and the automated assessment of suspicious lesions [12].

3.3. Skin Cancer

CAD systems based on deep convolutional networks demonstrate diagnostic performance comparable to that of experienced dermatologists. These findings are supported by recent reviews on hyperspectral imaging approaches for skin cancer detection [13].

However, challenges remain in terms of protocol standardization and clinical explainability (XAI).

4. Clinical Decision Support Systems (CDSS)

Clinical decision support systems have demonstrated proven effectiveness:

- they increase the detection of “red-flag” oncological symptoms in primary care [14];

- they improve diagnostic accuracy and accelerate clinical decision-making, contributing to higher patient-reported satisfaction [15];

- they enhance the routing and referral of patients across care pathways.

Despite these advantages, CDSS performance depends on:

- the quality of user interface design,
- the level of integration with medical information systems,
- the degree of trust among healthcare professionals.

5. Multimodal and Multi-Cancer Early Detection (MCED) Systems

Current trends indicate a rapid shift toward integrative diagnostic frameworks:

- multimodal models combining circulating cell-free DNA (cfDNA), methylation patterns, fragmentation profiles, and copy-number variations [16, 17];

- machine-learning models utilizing biomarker panels for ovarian cancer risk stratification and diagnosis [18–20];

– MCED blood-based tests capable of detecting dozens of cancer types from a single blood sample by analyzing genetic and epigenetic signals [21–24].

Studies published between 2023 and 2025 demonstrate the high diagnostic value and strong clinical potential of MCED approaches, particularly for cancers that are difficult to detect at early stages.

Based on the conducted analysis, a comparative overview of early-diagnosis technologies was prepared, as presented in Table 2.

Table 2. Comparison of Early Cancer Detection Technologies

Approach	Example Publications	Advantages	Limitations
Rule-based expert systems	[1], [7]	Simple implementation; transparent logical structure; fully interpretable rule sets	Limited diagnostic accuracy; no ability to learn from data
Fuzzy models (fuzzy rules, fuzzy soft-set, fuzzy neural networks)	[2], [3], [4], [5]	Robust performance under uncertainty and incomplete clinical data; good interpretability; resistance to noisy inputs	Moderate accuracy compared to deep learning models; complex tuning of membership functions
Classical ML (SVM, Random Forest, other machine-learning algorithms)	[10], [11], [12], [18]–[20]	Automated feature analysis; favorable balance between accuracy and computational efficiency; applicability to heterogeneous data types	Requires manual feature engineering; sensitive to the quality and balance of the training dataset
Deep Learning (CNN, DNN, transfer learning, ensemble DL models)	[6], [7], [8], [9], [10], [12], [13]	Highest diagnostic accuracy; automatic extraction of complex hierarchical features; particularly effective for medical image analysis	“Black-box” nature and low interpretability; requires large datasets and substantial computational resources
MCED systems and multimodal models (cfDNA, methylation, multi-omics profiling)	[16], [17], [21]–[24]	Ability to detect multiple cancer types from a single blood sample; high sensitivity at preclinical stages	High cost; lack of full standardization; limited accessibility; need for large-scale clinical validation

Based on the conducted analysis, the application of AI across different tumor localizations was evaluated, as presented in Table 3.

Table 3. Application of AI Methods Across Cancer Localizations

Localization	Methods	Sources
Breast Cancer	Fuzzy logic, fuzzy soft-set models, fuzzy neural networks, rule-based expert systems, classical ML, convolutional neural networks, transfer learning, CAD systems	[1]–[7], [8]–[11]
Lung Cancer	Neural networks, classical ML algorithms, DL-based models, elements of multimodal analytical pipelines	[12], [17]
Skin Cancer	Deep learning, CNN-based CAD systems, hyperspectral image analysis	[13]
Ovarian Cancer	Classical ML methods, multimodal models integrating clinical and molecular datasets	[18]–[20]
MCED (Multi-Cancer Early Detection)	cfDNA methylation profiling, copy-number variation, fragmentation patterns, multi-omics integration with ML/DL, liquid biopsy-based diagnostic frameworks	[16], [17], [21]–[24]

Based on the conducted analysis, a comparative assessment of the accuracy of AI methods using aggregated performance indicators was performed, which is presented in Table 4.

Table 4. Comparison of AI Methods by Average Accuracy

Method	Average Accuracy (%)	Comment
Rule-based systems	65–75%	Low diagnostic accuracy but high interpretability; based on early expert systems (e.g., Morio S., 1989 [1]).
Fuzzy logic / fuzzy rule-based models	78–85%	Perform well under uncertainty and remain stable in noisy environments (supported by [3], [4], [5]).
Classical ML (SVM, RF, kNN)	85–90%	High accuracy with well-engineered features; requires careful feature engineering (confirmed in [9], [10], [11], [12]).
Deep Learning (CNN, Transfer Learning)	92–96%	Demonstrates state-of-the-art performance on medical images; accuracy significantly improves with transfer learning (evidence from [9], [10], [13]).
MCED (cfDNA, multi-omics approaches)	94–98%	Highest early-stage sensitivity; capable of detecting dozens of cancer types from a single blood sample (based on [16]–[24]).

Based on the analysis, the use of AI methods by frequency of occurrence in the reviewed publications was evaluated, as presented in Table 5.

Table 5. Frequency of AI Methods Used in the Reviewed Studies

AI Method	Number of Publications	Percentage (%)
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Deep Learning	10	42%
Classical ML	6	25%
MCED	6	25%
Fuzzy Logic	4	17%
Rule-based Systems	1	4%

Based on the analysis, the advantages and limitations of AI methods were examined, as presented in Table 6.

Table 6. Advantages and Limitations of AI Methods in Early Cancer Detection

Method	Advantages (based on literature [1–24])	Limitations (based on literature [1–24])
Rule-based systems	High interpretability, simplicity, and full transparency of decision logic. Used in early diagnostic systems (e.g., Morio S., 1989 [1]).	Low diagnostic accuracy; no adaptability; unsuitable for large and heterogeneous datasets.
Fuzzy logic / soft-set models	Robust to noise, inherently interpretable, capable of handling incomplete, uncertain, and imprecise clinical data ([3–6]).	Lower performance on large, complex datasets; limited diagnostic accuracy compared with deep learning models.
Classical ML (SVM, RF, kNN)	High accuracy with proper feature engineering; fast inference; effective for structured clinical data ([7], [10], [11], [12]).	Requires manual feature engineering; sensitive to input data quality; limited ability to work directly with raw medical images.
Deep Learning (CNN, Transfer Learning)	Highest accuracy for image-based diagnostics: mammography, infrared thermography, dermatoscopy ([9], [10], [13]). Fully automatic feature extraction.	Requires large annotated datasets; low interpretability (“black-box” issue); prone to overfitting.
Multimodal ML/DL (clinical + imaging)	Highly versatile; integrates heterogeneous data types (clinical metrics, imaging, biomarkers). Demonstrated effectiveness in ovarian cancer and multi-omics research ([18], [19]).	High model complexity; requires large multi-source datasets; significant computational cost.
MCED (cfDNA, methylation, multi-omics)	Detects dozens of cancer types at early stages; very high sensitivity; deep biomarker informativeness ([21–24]).	Very high cost; lack of standardized protocols; limited accessibility; need for large-scale clinical validation.

The conducted analysis demonstrates that the use of intelligent technologies in early cancer diagnostics is evolving rapidly.

Rule-based systems laid the foundational principles of automated decision-making, fuzzy-logic approaches introduced interpretability and robustness in conditions of uncertainty, while ML/DL methods provided high accuracy in medical image analysis.

Multimodal and multi-cancer early detection (MCED) technologies have opened fundamentally new opportunities for population-level screening.

Modern expert systems possess significant potential; however, they still require broader clinical validation, standardization, and integration into routine medical practice.

Promising areas for future development include multimodal models that combine heterogeneous clinical and molecular data, explainable AI (XAI) technologies aimed at improving transparency and trust, and advanced MCED platforms capable of detecting multiple cancer types at preclinical stages.

Results

To develop an early cancer detection system, the following steps were implemented:

1. Construction of an expert knowledge base
2. Population of the knowledge base
3. Development of the mathematical module of the system
4. Creation of an application for expert use

Construction of the Expert Knowledge Base

As a result of the domain analysis, existing clinical diagnostic protocols for cancer detection were examined. Based on this review, the following variables were selected as system predictors: age, sex, smoking history, family oncological history, and frequency of respiratory infections.

The presence of an oncological disease was defined as the target (output) variable. For each predictor, value intervals were determined according to their contribution to the risk assessment.

Population of the Knowledge Base

A dataset containing responses from more than 1,000 patients was collected. These data were processed using methods of intelligent data analysis to identify meaningful patterns and structure the knowledge base.

Development of the Mathematical Module

A neural network was selected as the mathematical foundation of the system. Predictor values and corresponding outputs were exported into the MATLAB environment for computational modeling.

Three training algorithms were used for model development: Levenberg-Marquardt algorithm, Bayesian regularization method, Conjugate gradient method. For each algorithm, test metrics and prediction errors were obtained and analyzed (Figures 1–6).

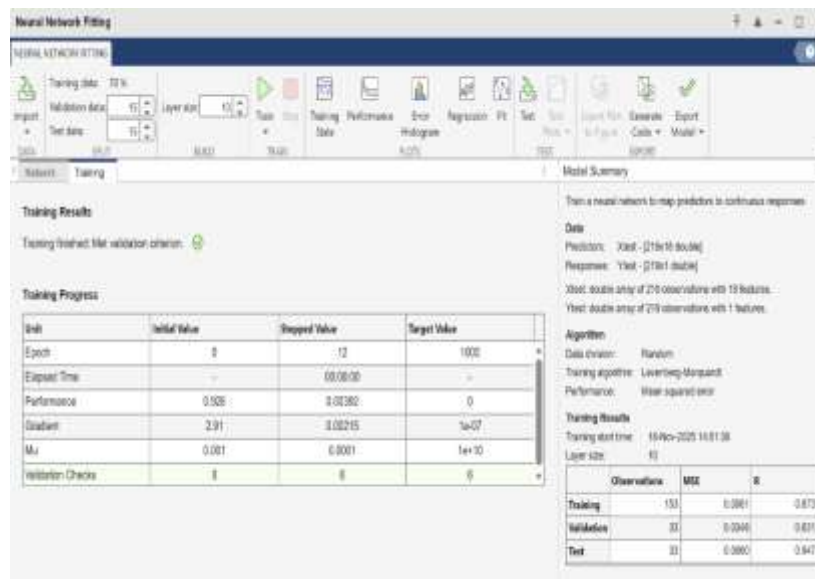


Figure 1. Implementation Using the Levenberg–Marquardt Algorithm

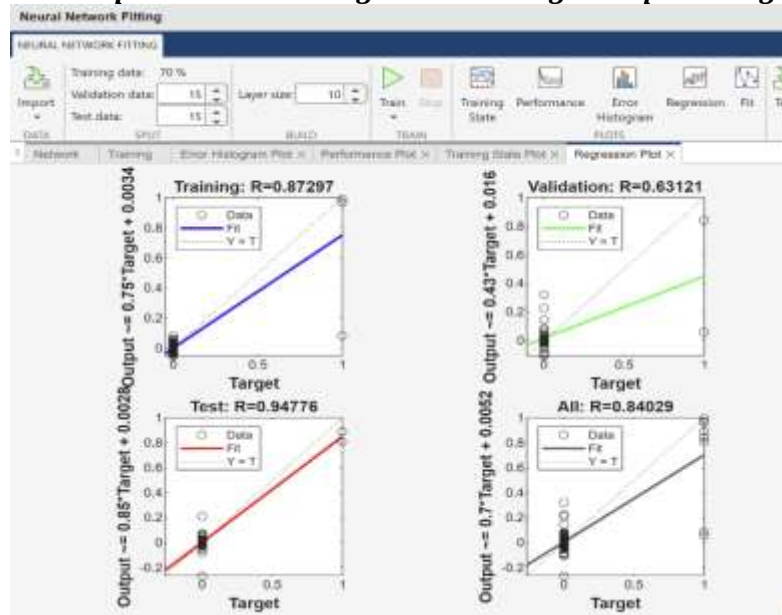


Figure 2. Training test values Implementation Using the Bayesian Regularization Method

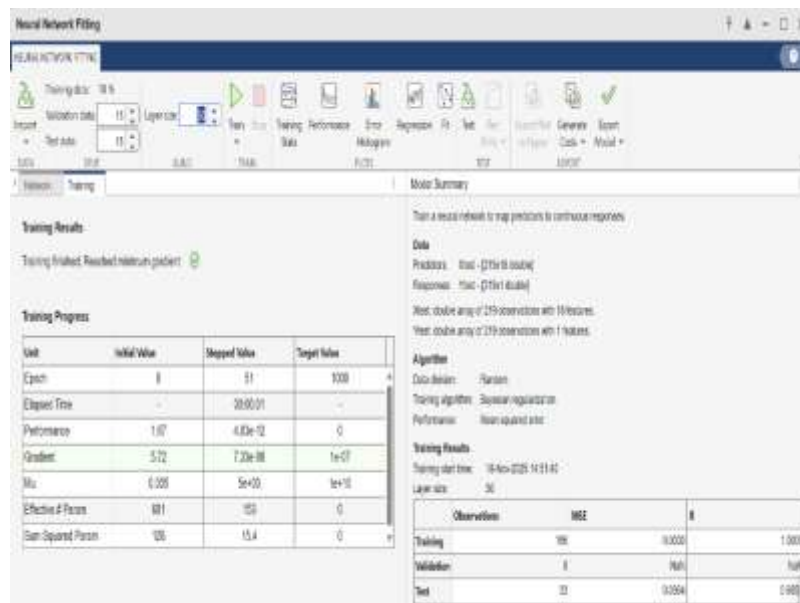


Figure 3. Implementation using the Bayesian Regularization method

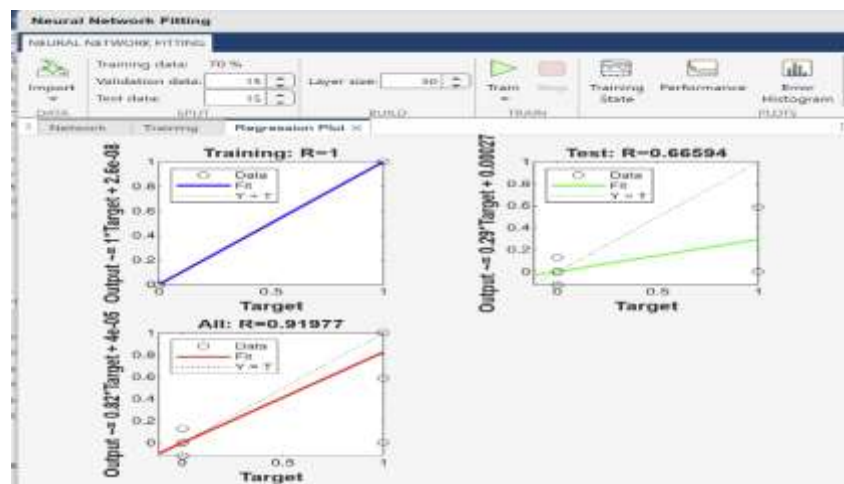


Figure 4. Training Test Values Implementation using the conjugate-gradient method

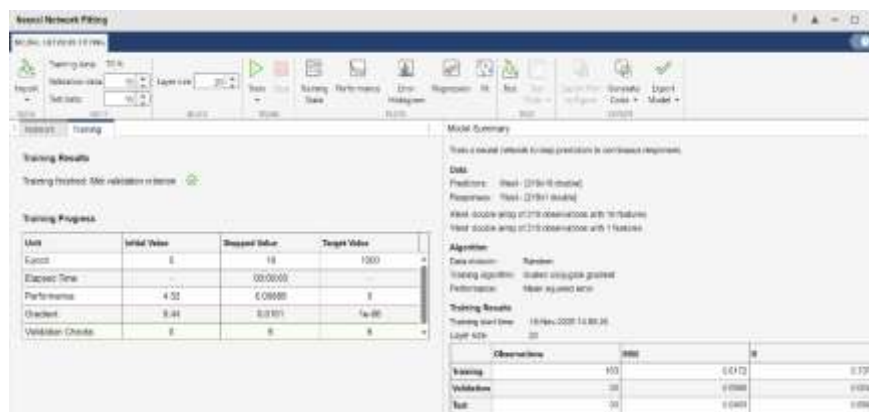


Figure 5. Implementation using the conjugate gradient method

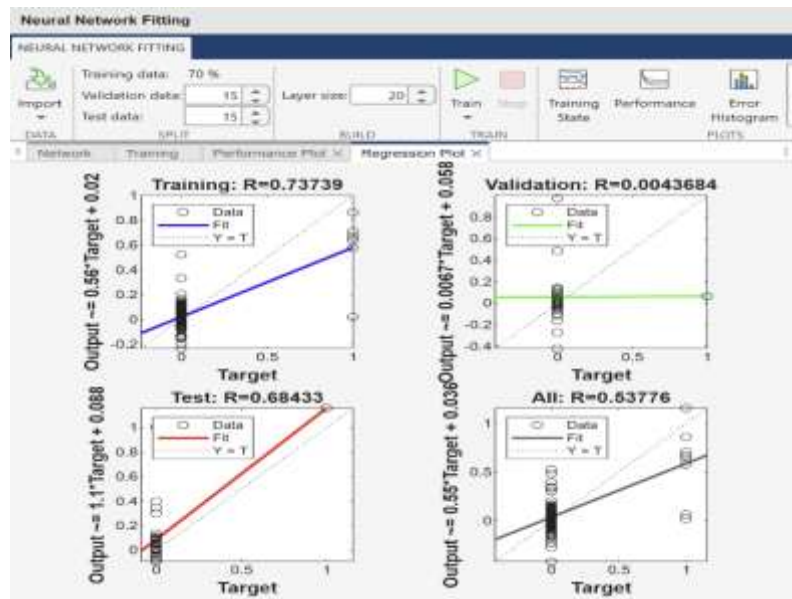


Figure 6. Training Test Values

Based on the obtained calculations, it can be concluded that the Levenberg-Marquardt algorithm is the most suitable for this task, as it provides the highest test performance values and demonstrates a learning curve that most closely follows the target data.

The structure of the proposed system can be represented as follows (Fig. 7)

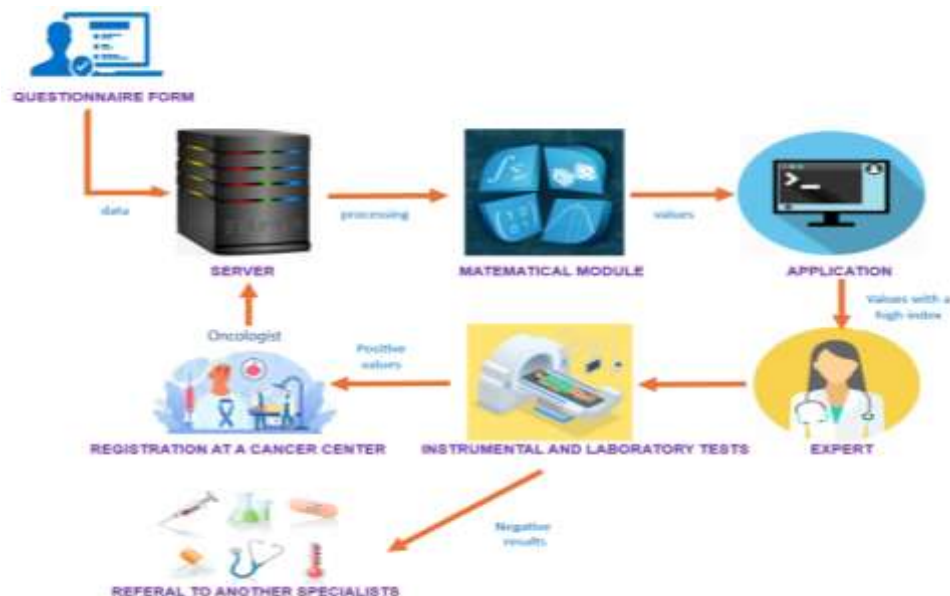


Figure 7. System structure

The system consists of the following components: a patient survey module, a data storage block, a mathematical computation module, an application interface, an oncologist expert module, an instrumental and laboratory diagnostics block, and an inference module.

The proposed system represents a prototype of an early cancer detection system based on an artificial neural network.

III. Conclusion

As a result of the conducted research, existing methods of early cancer diagnosis were thoroughly analyzed. Neural networks were identified as the foundational approach for building the expert system. A knowledge base was developed using the expertise of clinical oncologists. Key predictors for constructing the neural network model were determined. A mathematical model of the system was implemented in MATLAB using three algorithms: the Levenberg–Marquardt algorithm, Bayesian regularization, and the conjugate gradient method.

Based on the obtained computational results, it can be concluded that the Levenberg–Marquardt algorithm is the most suitable for this task, as it demonstrated the highest performance of the resulting function and provided a learning curve closest to the target values.

A structural architecture of an early cancer diagnostic system based on a neural network–driven expert system was proposed.

Future research will focus on developing a model employing deep learning techniques to achieve more accurate predictions of cancer probability.

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