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ANALYSIS OF THE ARCHITECTURE OF EXPERT SYSTEMS FOR CANCER DIAGNOSIS

Abstract. The article presents an analysis of the architecture of expert systems for cancer diagnosis based on modern artificial intelligence approaches. The key components of such systems are considered, including the knowledge base, inference mechanisms, user interface, and integration with multi-omic medical data. A comparative analysis of architectural solutions used in modern expert systems is carried out, and their advantages and limitations for early diagnosis and monitoring of cancer are identified. Particular attention is paid to machine learning methods that provide automatic knowledge updating and improve diagnostic accuracy. The results obtained can be used for further development of efficient, self-learning expert systems aimed at improving the quality of medical diagnosis and monitoring of patients with cancer.

Keywords: expert systems, cancer diagnostics, artificial intelligence, knowledge base, machine learning, multiomics data, medical monitoring, system architecture.

Cancer remains one of the leading causes of death in the world, and the fight against this disease requires increasingly innovative approaches. According to the World Health Organization (WHO), about 10 million people died of cancer in 2020. Lung cancer was the most common type in 2022 worldwide with 2.5 million new cases, which is 12.4% of the total number of new cancer cases. In second place are breast cancer in women (2.3 million cases, 11.6%), colorectal cancer (1.9 million cases, 9.6%), prostate cancer (1.5 million cases, 7.3%), and stomach cancer (970 thousand cases, 4.9%). Lung cancer was the main cause of death from cancer (1.8 million deaths, 18.7% of the total number of cancer deaths), followed by colorectal cancer (900,000 deaths, 9.3%), liver (760,000 deaths, 7.8%), mammary glands (670 thousand deaths, 6.9%) and stomach (660 thousand deaths, 6.8%) [1].

Timely detection and accurate diagnosis are decisive factors for the successful treatment of oncological patients. However, traditional methods of diagnosing cancer often take a long time, require highly qualified specialists and do not always guarantee accuracy. The human factor can cause false or late diagnoses, which negatively affects the prognosis of treatment. Thanks to the rapid development of artificial intelligence (AI), machine learning and deep learning technologies, new opportunities have opened up to optimize the process of cancer diagnosis. Expert systems based on these technologies are capable of automatically analyzing large amounts of medical data, including medical images (MRI, CT), genomic information, histological samples, and clinical records [2]. Thanks to fast data processing and high accuracy, these systems greatly facilitate the work of medical professionals, minimizing the possibility of errors and reducing the time needed to establish a diagnosis. In addition, expert systems can help doctors choose the optimal treatment strategy based on the analysis of millions of previous clinical cases. The role of such systems in the development of personalized medicine is especially important. Each patient has unique biological and genetic characteristics, so an individualized approach to cancer treatment becomes critically important. Expert systems are able to integrate different types of data – from medical images to genomic information – to create a detailed and accurate clinical picture of each patient. This allows you to determine the individual characteristics of the course of the disease and choose personalized treatment methods, which significantly increases the chances of success of the therapy. The purpose of this study is to evaluate the architecture of modern expert systems used for the diagnosis of cancer. The research focuses on the analysis of the architectural solutions used in such systems, their functionality, and the problems that these systems are designed to solve. In addition, an important aspect is the determination of the main directions of development of expert systems in the context of cancer diagnosis and their impact on modern medical practice.

Today, the use of computer technologies in the field of medical diagnostics has grown significantly. An expert system seeks information from its users to make recommendations. Expert systems are designed to solve complex problems by reasoning about knowledge, represented primarily as IF-THEN rules, rather than using a conventional procedural code [3]. MYCIN was the first known medical expert system developed by Shortliffe of Stanford University to help doctors prescribe antimicrobials for blood infections [4]. Some of the researchers developed an expert system for diagnosing coronary artery disease using myocardial perfusion imaging [5]; and an intelligent medical system for diagnosing bone diseases [6]. In this section, we will present the design of an expert system for dilatation diagnosiscardiomyopathy using CLIPS [4].

Expert systems are intelligent computer programs that use the knowledge and methods of artificial intelligence to solve complex problems in certain fields, in particular in medicine. At the heart of such systems are algorithms of machine learning, deep learning (deep learning), neural networks and other advanced methods of data processing, which allow them to analyze large volumes of medical data, including images, genomic information, histological samples and clinical records.

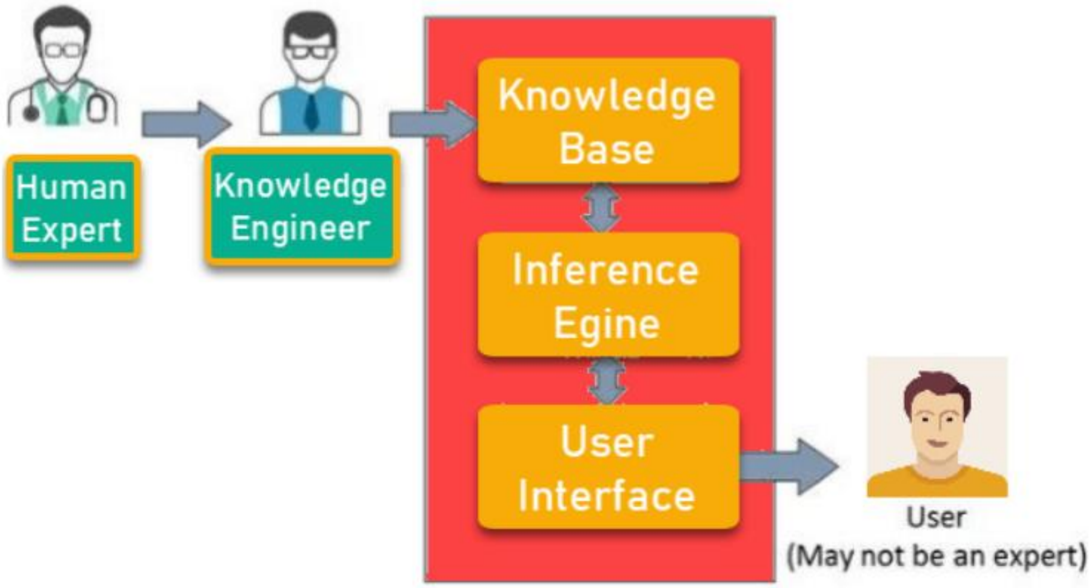

Fig. 1. Components of the expert system

In the field of cancer diagnosis, expert systems allow automating processes that previously required significant human resources and time. For example, medical image analysis systems, such as Watson for Oncology or PathAI, are able to help doctors detect tumors in the early stages, predict the outcome of treatment and offer recommendations for individual therapeutic approaches [7]. In addition, expert systems can integrate data from different sources (images, analyses, clinical studies), thus creating a single picture for more accurate and personalized treatment of patients. Thanks to the capabilities of artificial intelligence, expert systems help solve problems such as human errors during diagnosis, delays in processing large volumes of data, and difficulties in processing complex, multivariate medical data. At the same time, it is important to study and evaluate their architectural features in order to identify potential problems and limitations, as well as to determine prospects for their improvement and further development [8].

Nowadays, machine learning is a very common method of digitization. **Machine learning** - one of the sections of AI, algorithms that allow a computer to draw conclusions based on data without following rigidly set rules [9]. That is, the machine can find patterns in complex and multi-parameter tasks (which the human brain cannot solve), thus finding more accurate answers. As a result - correct forecasting. The main goal of machine learning models is to automate some of the processes to which this model is directed, therefore, first of all, the machine learning method consists in providing the most accurate predictions and results based on the input data analyzed by the software complex. Machine learning models consist of several main “whales”:

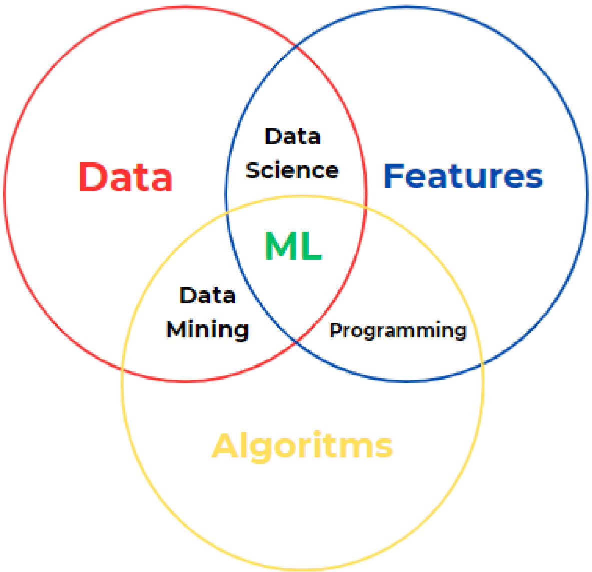

Fig. 2. Composition of machine learning models [10]

These are directly the data that are laid as input into the system itself, forecasts and algorithms. Data processing methods in machine learning are the basis for modern expert systems used in medicine, in particular for the diagnosis of cancer. One of the key tasks of machine learning in this context is classification, which allows the distribution of medical data into certain categories or classes. For example, the system can analyze medical images, such as MRI or CT scans, and classify them, determining the presence or absence of cancerous growths. Classification algorithms, such as neural networks or decision trees, can detect patterns in images or other types of data and help doctors make accurate diagnoses.

Another important technique in machine learning is regression, which helps predict numerical values. In the field of medicine, this approach is used to predict tumor growth, assess patient survival, and determine the likelihood of disease recurrence. Regression models make it possible to identify dependencies between various medical indicators and to form forecasts based on historical data, which contributes to more accurate decision-making in medical practice.

One of the leading technologies for cancer diagnosis is medical image processing using convolutional neural networks (CNN). These neural networks have a unique ability to recognize complex patterns in images, such as neoplasms, and detect them with high accuracy. CNNs can analyze images at different levels, highlighting key features, making them indispensable for automated cancer diagnosis [11]. Thanks to their ability to efficiently work with large amounts of data, such systems enable doctors to quickly obtain the accurate results needed to make informed treatment decisions. In addition to image processing, textual data analysis plays an important role in diagnostics. Medical records, case histories, and genetic reports contain a wealth of information that can be used to improve diagnosis and prognosis. Natural language processing (NLP) algorithms automate the analysis of such texts, highlighting important points and finding relationships, allowing doctors to receive the necessary recommendations. Thus, NLP complements the analysis of medical images, creating a more holistic picture of the disease. Predictive analytics is another important component of expert systems, as it not only helps in making a diagnosis, but also allows you to predict the results of treatment. For example, the system can analyze a patient's medical history and predict how he will respond to a certain treatment or what are the risks of disease recurrence. This gives doctors the opportunity to tailor treatment for each patient individually, based on data obtained from similar clinical cases.

All these technologies confirm that expert systems are complex software packages that use different data processing techniques to support medical decision-making. They are based on artificial intelligence and machine learning, which allows them to analyze large amounts of medical data and improve their diagnostic capabilities. Expert systems can process different types of medical information — images, text data, genetics — and integrate them to provide accurate and comprehensive results. Directly, any expert system consists of such structural blocks as a knowledge base, a conclusion module, a data interpretation module, a data entry interface, and explanation and training modules (Figure 3):

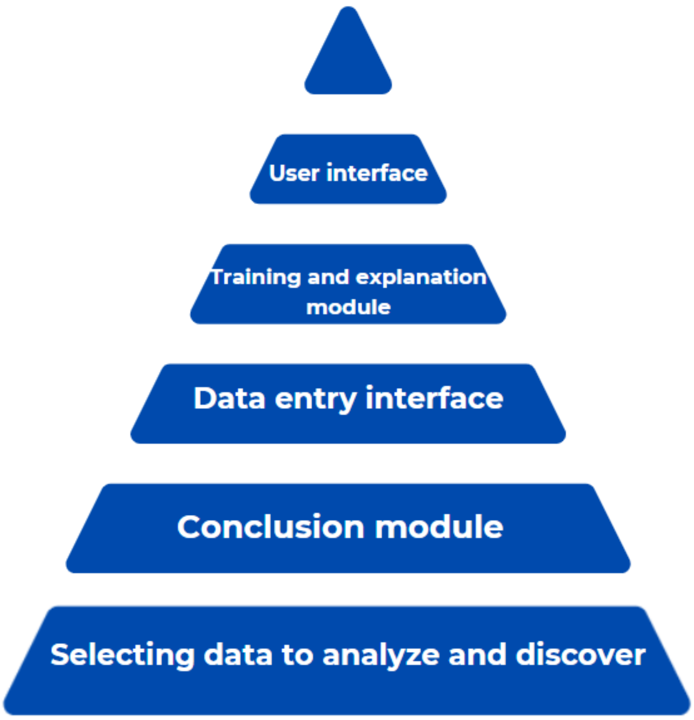

Fig. 3. Construction of expert systems for diagnostics

Expert systems are complex software complexes, the architecture of which includes several interconnected components. These components work together to enable the system to analyze data, make decisions, and support users in making complex decisions in a variety of industries.

Knowledge base is the foundation of any expert system. It is a source of specialized information that may include facts, rules, methods, scientific studies, and case studies. The knowledge base can be static (that is, filled manually by experts) or dynamic, when new knowledge is added automatically in the process of self-learning of the system. It should be well structured and logically organized so that the system can effectively use it to analyze data and formulate conclusions. A knowledge base can contain different types of information: from facts and descriptions to complex mathematical models. In medical expert systems, for example, the knowledge base may include medical protocols, diagnostic criteria, and data on previous clinical cases.

Conclusion module is the intelligent center of the system, which uses knowledge from the database to make decisions. It analyzes input data, matches it with existing information in the knowledge base, and applies rules or algorithms to formulate conclusions. This can be simple "if-then" logic or complex machine learning models using statistical methods or neural networks. The inference module works to find the optimal solution based on input data and existing knowledge. In medical expert systems, this module can compare a patient's symptoms with typical clinical cases and suggest diagnoses or therapeutic recommendations.

For the efficient operation of the expert system, it is necessary to ensure the possibility of entering the necessary data for analysis [12]. This can be either manual input (when the user provides information) or automatic loading of data from external sources such as medical images, laboratory results or text records. The quality of the entire system depends on the accuracy and structure of the entered data. The data entry interface must support different formats, which is especially important for medical expert systems that use different types of data (MRI, CT, biochemical indicators, etc.). This component ensures the transfer of data to the conclusions module, where their further analysis takes place.

Modern expert systems have the ability to self-learn and improve based on new data. The learning module allows the system to improve its predictions and recommendations by analyzing the results of previous diagnoses and decisions. This is especially important in conditions where new medical data or knowledge that was not previously taken into account appears. Machine learning in the training module can be both supervised (based on marked data) and unsupervised (independent study of patterns in the data) [12]. Thanks to this component, the system becomes dynamic and able to adapt to new conditions and challenges. To increase trust in the system, it is important that it can explain its decisions. The explanation module allows the user to understand on which data and logical operations the proposed solution is based. This is especially important in medical systems where diagnoses and recommendations must be substantiated. This module provides an explanation for each decision, allowing doctors or users to evaluate its validity and ensure that it is correct. It also helps in cases where system decisions need to be adjusted or questioned [12].

User interface is the component through which the end user interacts with the expert system. It should be intuitive, convenient and easy to use. The interface allows you to enter data, view analysis results, receive recommendations and explanations about the system solution. It is important that the interface provides quick access to all system functions. In medical expert systems, this component allows doctors to quickly receive test results, treatment or diagnosis recommendations, and review the system's decision history. The interface should be convenient for doctors and engineers, adapted to the specifics of their tasks. Architectural models of expert systems are used to ensure efficient collection, processing and interpretation of data. Some of the most common architectural solutions are classical rule-based systems, neural networks, and hybrid architectures that combine traditional methods with artificial intelligence technologies to improve diagnostics and other tasks.

Classic rule-based expert systems use production rules, which are among the earliest approaches to building such systems. In these systems, knowledge is presented in the form of "if-then" logical constructions formulated by experts. This approach is widely used in medical expert systems, where diagnostic decisions are based on known rules and recommendations. For example, if a patient is experiencing certain symptoms, the system can provide appropriate recommendations or diagnoses based on existing knowledge. For cases where the data is fuzzy or incomplete, fuzzy logic is applied, which allows the expert system to draw conclusions based on incomplete information. This approach is important in medicine, where symptoms can be vague and data partial. Neural networks, especially deep neural networks (Deep Neural

Networks, DNN), play a key role in modern expert systems, especially in cases of analysis of large volumes of data, such as medical images and text records [13]. One of the main types of neural networks used in expert systems are convolutional neural networks (CNN), which specialize in image analysis (Fig. 3) [13].

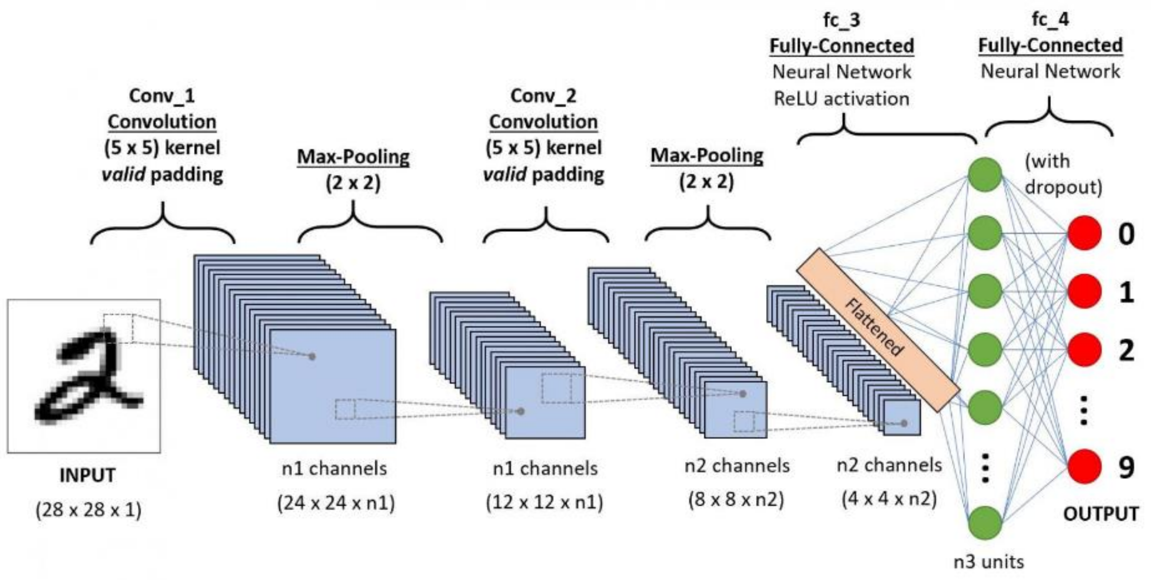

Fig. 3. Architecture of building a convolutional neural network of the classical type

The presented convolutional neural network (CNN) architecture is an example of a classic framework used for image analysis and classification. It consists of several key components, each of which performs important functions, from processing input data to making decisions based on classification. At the beginning, the image is fed to the input layer, where it is converted into numerical values corresponding to pixel intensities. Next, this data passes through several convolutional layers. The main purpose of these layers is to highlight image features. Convolutional layers use filters that are automatically adjusted as the network is trained. This allows them to recognize key image elements such as contours, shapes and other important patterns. Each convolutional layer is usually accompanied by pooling, most often it is a max-pooling operation, which reduces the dimensionality of the data, while leaving the most important features. This approach allows you to reduce computational costs and at the same time preserve essential information. Pooling also helps avoid overtraining, as reducing the dimensionality of the data makes the model more robust to noise. After passing through several convolutional and pooling layers, multidimensional data is transformed into a vector for further processing in fully connected layers. At this stage, the fully connected layers perform the final classification function by combining all the extracted features and applying activation functions such as ReLU. This allows the model to more effectively detect complex relationships between features and improve overall performance. The last component is the output layer, which is responsible for data classification. The number of neurons in this layer corresponds to the number of possible classification options, in this case it is numbers from 0 to 9. Based on the obtained results, the model makes a prediction about which number is depicted in the input image. CNNs enable the efficient recognition of patterns and abnormalities in medical images such as MRI or CT scans, making them extremely useful for cancer diagnosis. They use convolutional layers to extract key image features such as contours, textures and structures, which helps the system detect potential pathologies such as tumors or other abnormalities. Another important type of neural networks is Recurrent

Neural Networks (RNN), which are used to analyze sequential data, such as text records or time series data. RNNs allow systems to work with data that has a temporal or sequential structure, which is extremely important when analyzing textual medical records, disease histories, or patient treatment data. Hybrid expert system architectures combine traditional rule-based techniques with modern artificial intelligence technologies such as neural networks and machine learning. This approach allows you to use the advantages of both methods: on the one hand, the accuracy and reliability of classical rule-based systems, and on the other, the flexibility and adaptability of neural networks that can learn from large volumes of data and improve their predictions over time. For example, in medicine, such systems can use rules to determine preliminary diagnoses, after which neural networks refine these conclusions by analyzing more detailed medical images or textual data [13].

Modern expert systems based on artificial intelligence (AI) play a key role in the development of medicine, in particular in the diagnosis and treatment of cancer. By rapidly analyzing large amounts of medical data, these systems can significantly improve diagnosis accuracy, reduce decision-making time, and automate many routine processes that were previously performed solely by hand. This review will consider several specific systems that are already successfully used in practice: Watson for Oncology (IBM), PathAI, CaPTk (Cancer Imaging Phenomics Toolkit), and Arterys. Each of these systems has its own architecture and set of technologies that allow solving certain problems in the field of medical diagnostics.

One of the most well-known systems is Watson for Oncology, developed by IBM (Fig. 4) [15]. It is a machine learning-based system that specializes in the analysis of clinical cases in the field of oncology and helps doctors choose optimal treatment plans for patients. The architecture of Watson for Oncology is built on the use of large arrays of clinical data, scientific research and treatment protocols, which are integrated into the knowledge base of the system [16].

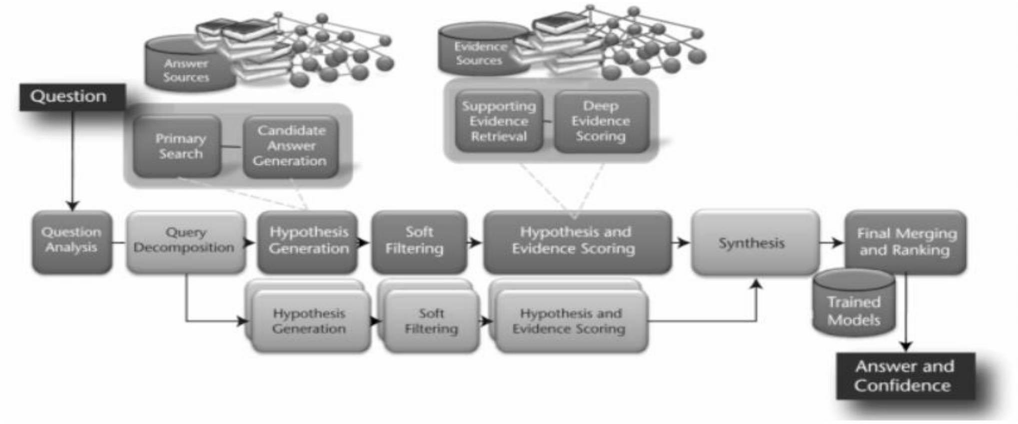

Fig. 4. Top-level architecture of the Watson for Oncology system

Based on this data, Watson analyzes the patient's symptoms, medical history and genetic data, and then suggests treatment options based on the latest protocols and research. Using natural language processing (NLP) techniques, the system can automatically analyze clinical records and scientific publications, allowing it to update its recommendations in real time. Watson for Oncology helps speed up the decision-making process, increasing the accuracy of diagnoses and reducing the likelihood of wrong decisions. This is especially important in the context of cancer, where timely and effective treatment can save patients' lives.

Another important system is PathAI, which specializes in automating the analysis of histological samples using deep learning. PathAI uses Convolutional Neural Networks (CNN), which is one of the most effective technologies for image analysis [17]. In the field of pathology, the analysis of histological samples is one of the most important and at the same time the most complex processes, which requires a high level of accuracy. PathAI's architecture allows the system to process thousands of histological images and automatically detect cancer cells with high accuracy. In addition, the system can analyze various pathological changes in tissues, which allows doctors to get a complete picture of the disease. PathAI significantly accelerates the diagnostic process, reducing the burden on pathologists and minimizing the number of false-negative or false-positive results. Another advanced system is CaPTk (Cancer Imaging Phenomics Toolkit), which is a cloud-based platform for the analysis of medical images using artificial intelligence methods. CaPTk is designed to work with medical images such as MRI or CT and provides analysis of various phenotypic characteristics of tumors. The architecture of this system is built on the basis of machine learning, which allows it to automatically recognize cancerous formations, as well as predict the development of tumors based on the available data.

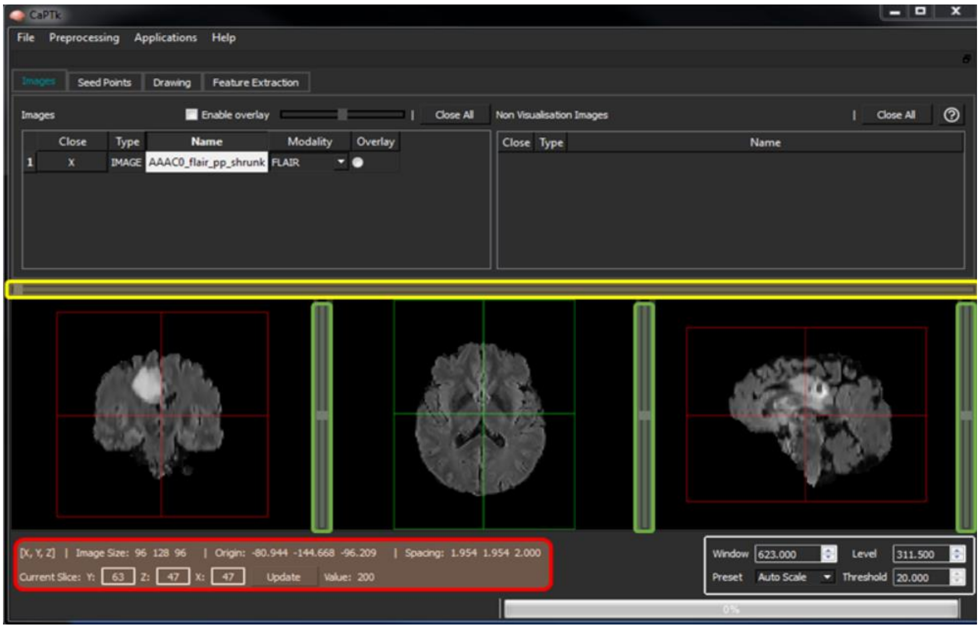

Fig. 5. Visualization of MRI data analysis in the Cancer Imaging Phenomics Toolkit system [18]

One of the key features of CaPTk is the integration of multiomic data, including information from different sources (images, genetic data, clinical records), which allows the system to obtain more complete results. This platform provides doctors with the tools to make more accurate predictions and choose treatment strategies based on the analysis of large amounts of data.

Arterys is an innovative cloud-based solution for real-time medical image analysis. This system uses machine learning and cloud computing to process large volumes of medical images at high speed. One of the advantages of Arterys is the ability to analyze images in real time, which allows doctors to receive results immediately after performing diagnostic procedures. In addition, the system automatically integrates with electronic medical records, which ensures seamless data exchange between doctors and other participants in the medical process. Arterys allows accurate visualization and evaluation of various types of cancer, which significantly increases the efficiency of diagnosis and treatment.

The general problems that these systems solve relate to three main areas. First, they contribute to a significant acceleration of the diagnostic process. By automating the analysis of medical images and text records, doctors are able to make faster decisions, which are critical in cases with cancer patients. Secondly, these systems increase the accuracy of diagnosis, reducing the number of false-positive and false-negative results. Because AI-based systems are able to analyze vast amounts of data and detect complex patterns, they can provide more accurate diagnoses than traditional methods that rely on human factors. Third, these systems automate many routine processes and help doctors make decisions. This allows doctors to focus on more complex cases that require their immediate attention, while systems automatically analyze common cases or routine procedures. Modern expert systems based on artificial intelligence demonstrate significant success in automating diagnostics and increasing the accuracy of medical decisions. However, despite the achievements of systems such as Watson for Oncology, PathAI, CaPTk and Arterys, there are a number of challenges that require further research. In particular, these systems face difficulties when working with incomplete or heterogeneous data, and are also highly dependent on large amounts of labeled data for training. This indicates the relevance of research in the direction of creating self-learning systems capable of learning without the constant need for labeled data. Such systems can significantly reduce the amount of reference data required for training by using self-learning techniques to analyze raw information that contains important features for diagnosis. In addition, the analysis of multi-omic medical data — which includes different types of data such as imaging, genomic information, protein profiles, and clinical records — provides new opportunities for more accurate monitoring and prediction of disease progression. A self-learning system that integrates these various types of medical data can not only improve the accuracy of early diagnosis, but also help predict the course of the disease. It is also important that such a system reduces the burden on medical personnel and increases the efficiency of the treatment process, allowing to automate routine tasks and focus the attention of doctors on more complex cases. Thus, further research in this direction is not only scientifically significant, but also able to significantly improve the quality of medical care in the field of oncology.

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