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# Development of the architecture of a computer aided diagnosis system in medicine

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## ABSTRACT

With the development of information technology, automation of various production processes is an urgent task, and medical diagnostics is no exception. In recent decades, artificial intelligence and information technology have been widely used in computer diagnostic systems. However, as technology advances, so do the challenges. Not every system is optimized and fast, and traditional methods are fading into the background. Often, systems do not use cloud technologies and have unoptimized architectures. This all affects their performance and, accordingly, is an urgent problem. The study analyzes the methods used in computer diagnostic systems and compares them in terms of advantages and disadvantages. The scientific works related to computer diagnostic systems in medicine for specific tasks are analyzed. The existing architectures of computer diagnostic systems are analyzed, which made it possible to identify the use of consistent approaches to diagnosis. Based on the analyzed data, the purpose, objectives, object and subject of the study are determined. A new architecture has been developed that uses the capabilities of U-Net for image segmentation and convolutional neural networks for medical image classification. The developed architecture is designed to increase the speed and automation of diagnostic processes through the use of neural networks and, accordingly, reduce human intervention. The scientific novelty of the developed architecture lies in the parallel execution of medical image segmentation and classification tasks, which gives a potential increase in data processing speed, and in the availability of an image generator, which solves the problem of lack of test data for model training.

**Keywords**: Computer-aided diagnosis; decision support systems; image analysis; image detection; neural networks; medicine

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## INTRODUCTION

The rapid development of technology, and especially artificial intelligence, in recent decades has opened up wide opportunities for the medical industry to implement computer-aided diagnostic systems.

CAD (Computer Aided Diagnosis) is a computer diagnostic system that helps in the process of diagnosing diseases by analyzing medical images. Such a system is able to automatically detect signs of pathology.

Such systems can use diagnostic rules to emulate the way a doctor makes a diagnosis. In this sense, these systems function as expert systems or decision support systems.

DSSs (Decision Support Systems) are computerized systems that help doctors and medical staff make informed decisions in the treatment and diagnosis process. They can analyze patient data, compare it with data contained in medical databases, make recommendations for diagnosis or treatment,and thereby increase the efficiency and accuracy of medical decisions.

It is important to understand that DSS are advisory in nature.

The main goal of CAD is to automate the process of detecting anomalies in medical images. DSS is broader in functionality and includes assistance in decision-making based on a large amount of data. This is the difference between the two systems.

In modern medicine, computer-aided diagnosis systems are becoming increasingly important due to their ability to improve diagnostic accuracy and increase treatment efficiency.

## 1. ANALYSIS OF LITERARY DATA AND PROBLEM STATEMENT

The progressive development of computer-aided diagnosis (CAD) and decision support systems (DSS) in medicine is largely dependent on the evolution of architectures and methodologies used in medical image analysis and patient data processing. This analysis covers a number of studies, each focusing on different approaches to improving the accuracy, efficiency, and clinical applicability of these systems.

All computer-aided diagnosis systems are based on the use of the following methods: traditional methods, machine learning, and deep learning.

Traditional CAD methods include the use of image processing algorithms to detect anomalies. For example, image segmentation, contour extraction.

Machine learning allows you to create models that learn from historical data. The most common algorithms are decision trees, support vector machines (SVMs), and ensemble methods.

Deep learning uses multilayer neural networks to automatically extract features and classify data. Popular architectures include convolutional neural networks (CNNs) and recurrent neural networks (RNNs).

A comparison of the advantages and disadvantages of these methods is shown in Table.

An analysis of different CAD system methods shows that each approach has its advantages and disadvantages, which should be taken into account for a specific task and architecture choice. Traditional image processing methods are easy to implement and fast, but their accuracy is often insufficient for complex diagnostic tasks (Fig. 1).

Machine learning provides more flexibility and accuracy, but requires large amounts of data and always has a risk of overfitting. Deep learning allows for the highest accuracy due to its ability to automatically extract relevant features, but requires significant computing resources and training time.

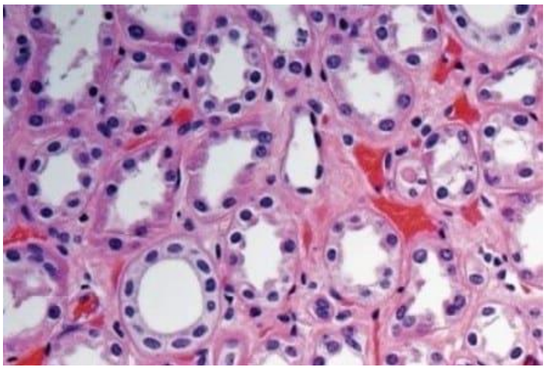
In general, the choice of methods depends on the specific requirements for the computer diagnostic system, such as the required accuracy, availability of computing resources and amount of available data.

Already published scientific papers describe the development and improvement of computerized diagnostic systems for various diseases.

*Table.* **Advantages and disadvantages of CAD methods**

| **Methods** | **Advantages** | **Disadvantages** |
|---|---|---|
| Traditional methods | - Easy to implement;<br>- Fast execution (do not require significant computing resources, so processing is fast);<br>- Low requirements for computing resources (the use of simple algorithms does not require powerful hardware) | - Limited accuracy (accuracy deteriorates when analyzing complex or low-quality images);<br>- Dependence on image quality;<br>- Low adaptability (methods often require manual adjustment of parameters for each specific task) |
| Machine learning | - Flexibility in model customization;<br>- The ability to use a large amount of data (the more data is used for training, the higher the model accuracy can be) | - The need for a large amount of reference data (a large amount of training data is difficult to obtain);<br>- Risk of overtraining (models can overlearn on training data and perform poorly on new, unfamiliar data) |
| Deep learning | - High diagnostic accuracy due to complex multilayer neural networks;<br>- Automatic feature selection (networks independently extract relevant features from the data, which reduces the need for manual intervention);<br>- Ability to work with large amounts of data | - High demands on computing resources (training deep neural networks requires powerful GPUs and a large amount of RAM);<br>- Complexity of setup (requires high qualification and understanding of complex algorithms);<br>- Long model training time |

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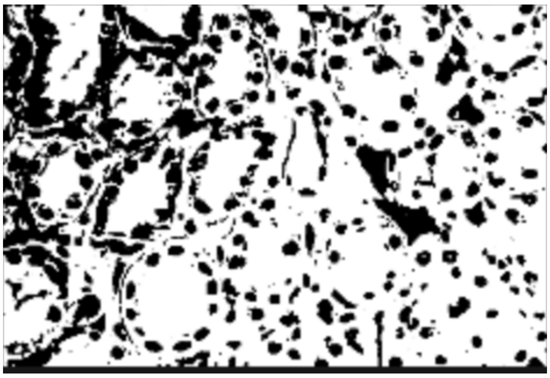
b

*Fig. 1.* **Example of threshold segmentation:**
**a – original histology image;**
**b – segmented image using threshold**
**Source: compiled by the authors**

The authors of [1] conduct a detailed analysis of computer diagnostic systems and focus on the range of their capabilities. They also analyze the key developments that have led to the current state of this industry.

Paper [2] describes the principles of designing a computerized diagnostic system based on two examples. The first one focuses on differentiating between symptomatic and asymptomatic carotid atheromatous plaques. The second CAD presented in this article supports the diagnosis of focal liver lesions and is able to characterize liver tissue on computed tomography images as normal, hepatic cyst, hemangioma, and hepatocellular carcinoma.

The authors of [3] describe a comprehensive CAD architecture for lung observation and nodule detection. Central to this architecture are the analytical components: an automated nodule detection system; nodule tracking and volume measurement capabilities that are integrated into a data management system that includes image acquisition and archiving mechanisms; a database for storing quantitative nodule measurements and visualization; and reporting tools.

The authors of [4] developed two different programs for quantifying collagen content and blood vessel density. The work is devoted to the identification of common subtypes of meningiomas.

Paper [5] provides a detailed overview of clinical applications and two commercial algorithms. Clinical applications can be grouped as computer-aided diagnosis, individual prognosis, functional assessment, segmentation of radiological structures, and optimization of data acquisition.

Paper [6] describes the use of two commercial CAD systems to evaluate screening mammography. The authors concluded that the architectures need to be improved, as in some cases, the images were incorrectly evaluated.

The authors of [7] identified seven main problems that arise in computerized diagnostic systems today.

Paper [8] proposes a new resource-efficient model, EfficienetNetB4, which includes the functions of a local binary template to improve the accuracy of cancer detection.

The authors of [9] propose a method for automatic detection of microaneurysms.

The authors of [10] propose a CAD system for diagnosing breast cancer using a deep belief network that automatically detects breast areas and recognizes them as normal, benign, or malignant.

The authors' research in [11] focuses on the design and development of a medical imaging and analysis system using digital image processing tools and artificial intelligence methods that can detect anomalies, classify them, and provide visual evidence to radiologists. All stages of diagnosis are performed sequentially.

The authors of [12] propose a new architecture based on recurrent and deep neural networks for medical image analysis called Bi-xBcNet-96.

Paper [13] provides a comprehensive overview of the clinical aspects of breast cancer, such as risk factors, breast abnormalities, and BIRADS (Breast Imaging Reporting and Data System). This paper also introduces CAD systems that have been recently developed for breast cancer segmentation, detection, and classification. The paper also discusses an overview of mammography datasets used in the literature and the challenges of applying CNNs to medical images.

In [14], the authors propose an efficient and fully automated CAD based on deep learning techniques supported by XAI (explainable artificial intelligence) methods for the accurate examination and diagnosis of breast cancer using ultrasound images. The proposed CAD includes four main steps: preprocessing, segmentation, XAI, and feature extraction. All of them are performed sequentially.

The authors of [15] propose a new adaptation of the EfficientNetv2 architecture.

Paper [16] is devoted to the development of a neural network system that allows for the automatic diagnosis of brain tumors based on MRI images and the selection of important areas. The application aims to speed up diagnostics and reduce the risk of missing a neoplastic lesion.

Study [17] presents a CAD system based on quantum deep learning for COVID-19 binary image classification, where the ResNet50 model is first used to train weighting coefficients on a multi-class chest dataset and later implemented on the COVID-19 binary classification dataset to compare performance with its hybrid quantum counterpart.

Paper [18] describes a CAD system for diagnosing skin cancer based on the DLCAL-SLDC model.

Researchers also describe neural network architectures for detecting various diseases, including Alzheimer's disease [19, 20], epilepsy [21], and Parkinson's disease [22].

In [23], the authors propose their architecture for diagnosing breast cancer. The InBreast dataset was used for the test. All stages of diagnosis in the system are performed sequentially.

According to the literature review, the use of neural networks is quite a popular tool, and many systems use sequential approaches. In addition, the analyzed scientific works use the same datasets for training models. Based on this, it is an urgent task to develop a CAD architecture that would potentially increase the speed of the system through parallelism and solve the problem of the amount and originality of test data for training neural networks by integrating an image generator into such a system.

The research group led by Professor Oleh Berezsky at the Western Ukrainian National University has been working on the application of artificial intelligence in computer diagnostic systems for twenty years. A number of scientific papers by the research group reflect methods, algorithms, and software tools for diagnostics in oncology [24, 25], [26, 27], [28, 29], [30, 31].

## GOAL AND RESEARCH OBJECTIVES

**The purpose of the research.** The aim of the study is to develop a CAD architecture based on neural networks.

**The objectives of the research are as follows:** analysis of existing CAD and DSS architectures and their comparison; analysis of commercial CAD and DSS.

**The object of research** diagnostic process in CAD systems.

**The subject of research** is the architecture of CAD systems.

## 2. MAIN RESEARCH RESULTS

The basic CAD architecture consists of four main modules [32]:

1. Image preprocessing
2. Definition of region of interests
3. Feature extraction and selection
4. Classification.

*Image preprocessing*. The basic idea of image processing is to create better quality data by applying certain techniques. These include: smoothing methods, which include the use of average filters, median filters, Laplace filters, and Gaussian filters; improving the edges of image structures, which includes smoothing and wavelet transforms; and increasing the contrast of an image, which includes histogram equalization.

*Definition of region of interests*. Normal and abnormal anatomical structures that can be detected in patient images can be identified using manual (semi-automated) or fully automated methods. One example of a semi-automated method that is widely used to identify regions of interest in medical images is the Seeded region growing method. An automated methodology includes active contour models that automatically detect and track anatomical contours in two-dimensional (2D) medical images due to their ability to accurately approximate random organ boundary shapes.

*Feature extraction and selection*. Feature extraction can be performed in the spectral or spatial domain. During feature extraction and separation, various quantitative measurements of medical images are performed to make decisions about the pathology of a structure or tissue. After feature extraction, a subset of features is selected, and the most reliable ones are chosen to reduce the overall complexity and increase the classification accuracy.

*Classification*. Assigning a set of features to the appropriate class is one of the most common tasks in feature recognition in image analysis. Classification of features from a given set can be supervised or unsupervised. In supervised classification, the feature set is a member of a predefined class, while in unsupervised classification, the feature set template belongs to an unknown class. Supervised classification can be based on statistical classifiers, such as decision trees, nearest neighbor classifiers, Bayesian classifiers, and neural networks [32].

Another typical CAD system architecture is shown in Fig. 2. First, the system receives the data received by the doctor from the patient, and then processes it as follows: pre-processing, segmentation, identification of areas of interest, evaluation, and classification [33]. The next step is to make a diagnosis and prescribe treatment.

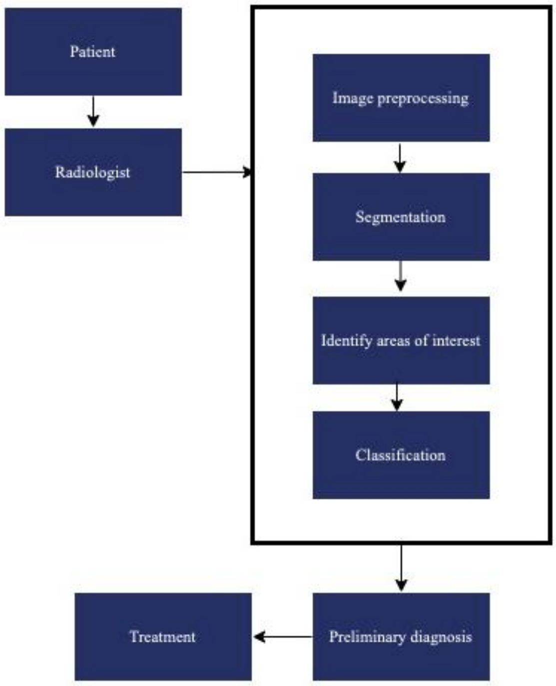


*Fig. 2.* **Architecture of CAD system**
**Source: compiled by the authors**

From the above, we can conclude that all existing computer-aided diagnosis systems have a similar or identical architecture. CAD differ only in the methods of operation used to process information.

A description of the DSS architecture is given below.

The heart of this system is the Patient Model, which contains certain patient data, such as medical history, health parameters, measured results, etc.

The Treatment Library consists of a list of treatments with corresponding procedures, variables, and a set of rules used to determine the likely impact of the treatment on the specified patient health parameters. Treatments can be marked as safe or unsafe for certain patient conditions.

Intelligent Agents use inference methods to optimize a treatment or set of treatments.

The Authenticated Knowledge Base is used to update both patient models (with newly discovered parameters and relationships between parameters and disease), patient models (with newly discovered or injuries), and the treatment library (with new treatments, new side effects, and new ways to apply old treatments).

In turn, knowledge is provided by the scientific community through publications in journals and conferences, as well as through data mining from existing electronic health records [34].

Since DSS also performs some image analysis, it can be said that the decision support system also includes the functionality of a computer diagnostic system.

### 2.2. Commercial CAD and DSS in oncology

Commercial CAD in oncology includes solutions for detecting cancerous tumors in various parts of the body, such as the breast, lungs, and gastrointestinal tract.

The most popular systems are Zebra Medical Vision and Aidoc, whose architectures (Fig. 3) are similar.

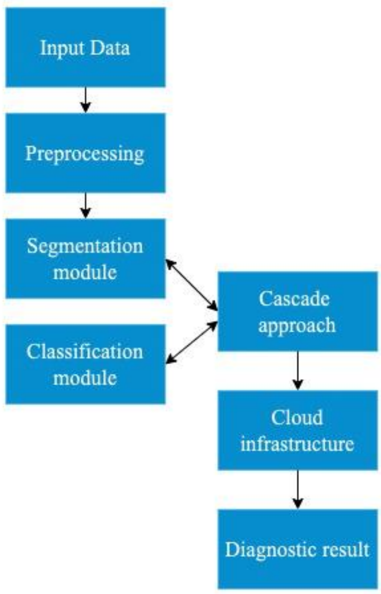


*Fig. 3.* **General architecture of Zebra Medical Vision and Aidoc**
***Source*: compiled by the authors**

It is worth noting that both use U-Net networks for image segmentation and CNNs for classification. Both systems have a cascade approach, i.e., several models work in sequence to improve the accuracy of the result. These systems utilize cloud technologies to process large amounts of data and access it quickly. However, as you can see from the figure, each stage is performed sequentially, which is not very good in terms of data processing speed.

### 2.3. Development of a new CAD system architecture

The system consists of several well-defined modules, each of which performs a specific function (Fig. 4). This modularity allows the system to be more flexible and easily adapt to different types of medical images. The system is built using cloud technologies, which gives better accessibility and unlimited computing resources, of course, it is not free.The database contains original histological and immunohistochemical images, synthesized images, and image segmentation masks. As you can see from Fig. 4, the system also has an image generator that works on the basis of diffusion models. It is needed to cover the issue of lack of test data for training the segmenter and classifier.

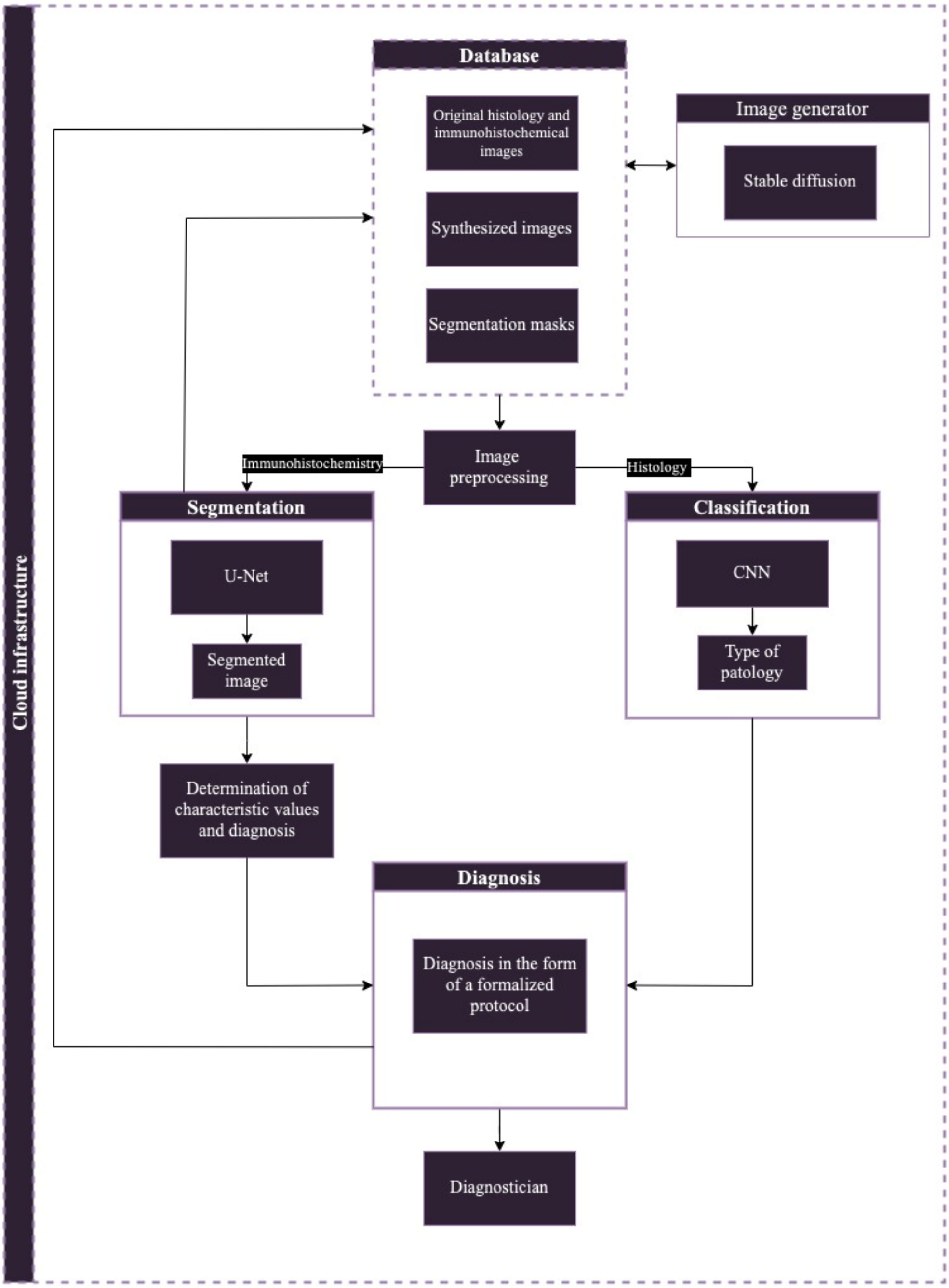


*Fig. 4*. **Developed CAD architecture**
***Source*: compiled by the authors**

The pre-processing module improves the input images to increase the accuracy of further segmentation and classification.

Immunohistochemical images will be fed to the segmenter. Segmentation is based on the use of U-Net networks, which are characterized by the fact that they allow you to accurately identify objects in images with high spatial resolution. Segmentation results are used for informative tissue analysis and play an important role in identifying areas of interest with a high probability of pathology. The output of U-Net gives us segmented images, after which the system determines quantitative characteristics and makes a diagnosis based on certain rules.

For classification, histological images will be submitted as input. Each histological image corresponds to four immunohistochemical images. After classification, we will be able to get a certain class and subclass or a certain type and subtype of pathology.

Based on the results of segmentation, classification, and calculated quantitative characteristics, the system issues a diagnosis in the form of a specialized report that the diagnosing doctor receives.

It is worth noting that segmentation and classification work in parallel.

Here are the following conclusions:

1. Thanks to the image preprocessing module, the system is able to improve the quality of input data, which increases the accuracy of subsequent analysis stages. This is an important step, as image quality directly affects the accuracy of segmentation and classification.

2. The use of an image generator based on stable diffusion solves the problem of lack of tessellation data for segmentation and classification.

3. The use of U-net networks for image segmentation emphasizes the high accuracy and efficiency of the system in identifying relevant segments. This is especially important in medical diagnostics, where segmentation can help identify pathological formations or other key structures.

4. The classification module, which uses convolutional neural networks, allows the system to automatically determine the type and subtype of pathologies. This greatly increases the efficiency and speed of the doctor's work, as the system can quickly provide preliminary results that the doctor can check and refine.

5. Segmentation and classification work in parallel, which gives a potential increase in data processing speed.

6. The proposed system architecture works using cloud technologies, which, in turn, gives more flexibility in the choice of hardware resources.

## DISCUSSION OF RESULTS

Based on the study, it can be concluded that both traditional and neural network-based methods are used depending on the tasks and limitations. Traditional approaches require fewer resources and are useful in cases of limited computing power. Modern neural network methods, such as U-Net, provide high accuracy in

detecting pathologies in medical images, but require more resources, both training (test datasets) and hardware. The developed architecture makes it possible to solve the problem of lack of test data.Commercial CAD and DSS systems in oncology, such as Zebra and Aidoc, are already widely used in clinical practice. They demonstrate high efficiency in helping doctors make decisions regarding the diagnosis and treatment of cancer.

To achieve high security, commercial CAD systems use data encryption and anonymization, compliance with certain standards (HIPAA – Health Insurance Portability and Accountability Act or GDPR – General Data Protection Regulation), access control, and audits. If the system operates using cloud technologies, such as AWS, Google Cloud, or Microsoft Azure, its security is enhanced, as these providers have a high level of security certification.

The further development and implementation of CAD systems in medical practice has great potential to improve the accuracy of diagnosis and the quality of treatment of diseases. This is possible with close cooperation between information technology developers and medical experts.

## CONCLUSIONS

1. The existing architectures of computer-aided diagnosis systems in medicine, such as CAD and DSS, were analyzed, which made it possible to study the features of each of them for further development of their own architecture.

2. We analyzed commercial CAD and DSS architectures. This allowed us to choose the best way to develop our own architecture.

3. A CAD architecture based on the use of U-Net networks for segmentation and CNN networks

for classification of medical images has been developed, which allows automating the diagnostic process in medicine.

4. The novelty of the developed architecture lies in the potentially faster image processing due to the parallel segmentation and classification and the availability of an image generator, which makes it possible to solve the issue of lack of test data for model training.

5. The use of cloud technologies can increase the security and availability of the system.

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# Розробка архітектури системи комп'ютерного діагностування в медицині

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## АНОТАЦІЯ

З розвитком інформаційних технологій актуальним завданням є автоматизація різних процесів виробництва, навчання і медична діагностика не є виключенням. В останні десятиліття штучний інтелект та інформаційні технології широко використовуються в системах комп'ютерного діагностування. Проте, з розвитком технологій, складнішими стають і завдання. Не кожна система є оптимізованою та швидкою, традиційні методи відходять на другий план. Часто системи не використовують хмарні технології, мають неоптимізовані архітектури. Це все впливає на їхню роботу і, відповідно, є актуальною проблемою. У дослідженні проведено аналіз методів, що застосовуються у системах комп'ютерного діагностування, зроблено їх порівняння з точки зору переваг та недоліків. Проаналізовано наукові праці, що стосуються систем комп'ютерного діагностування в медицині для виконання специфічних завдань. Проведено аналіз існуючих архітектур систем комп'ютерного діагностування, що дало змогу виявити використання послідовних підходів для діагностування. На основі проаналізованих даних визначено мету, завдання, об'єкт та предмет дослідження. Розроблено нову архітектуру, яка використовує можливості U-Net для сегментації зображень і згорткових нейронних мереж для класифікації медичних зображень. Розроблена архітектура призначена для підвищення швидкості та автоматизації діагностичних процесів за рахунок використання нейронних мереж та, відповідно, зниження участі людини. Наукова новизна розробленої архітектури полягає у паралельному виконанні завдань сегментації та класифікації медичних зображень, що дає потенційний приріст у швидкості опрацювання даних та у наявності генератора зображень, що дає змогу вирішити проблему нестачі тестових даних для тренування моделей.

**Ключові слова:** системи комп'ютерної діагностики; аналіз зображень; розпізнавання зображень; нейронні мережі; медицина

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