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METHOD FOR INTERPRETING DECISIONS MADE BY DEEP LEARNING MODELS

The use of artificial intelligence (AI) in medical diagnostics opens new opportunities for analyzing complex medical images and optimizing diagnostic processes. One of the key challenges remains the interpretation of results obtained through AI systems, particularly in medical practice, where ensuring transparency and clarity of decision-making is critically important. This study proposes a method for visualizing and interpreting the results of cardiac disease classification based on MRI image analysis using deep learning models. The primary goal of the research is to explain AI-driven decisions in a convenient and understandable format for physicians, contributing to the reduction of subjectivity in clinical practice.

During the research, approaches were developed for visualizing key groups of medical indicators, such as heart volumes, ejection fraction, myocardial wall thickness, and volume-to-mass ratios. The study describes numerical metrics commonly used in medical practice. Fifteen key medical metrics were identified and grouped into corresponding categories for effective representation of essential medical indicators. Various visualization forms were utilized to ensure intuitive data presentation: pie charts to demonstrate ratios, the 17-segment myocardial model for analyzing wall thickness, and numerical indicators for accurately displaying volumes and ejection fraction. This approach allows physicians to quickly assess structural changes in the heart and make informed conclusions.

The proposed method aims to enhance transparency and trust in AI by providing comprehensible data representation, reducing the risks of subjective interpretation and cognitive biases. The results indicate that using such visualizations can significantly facilitate clinical decision-making, improve diagnostic accuracy, and standardize approaches to medical data analysis.

Keywords: Cardiac MRI, heart pathology, deep learning, classification, interpretation.

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МЕТОД ІНТЕРПРЕТАЦІЇ ОТРИМАНИХ, ЗА МОДЕЛЯМИ ГЛИБОКОГО НАВЧАННЯ, РІШЕНЬ

Використання штучного інтелекту (ШІ) у медичній діагностиці відкриває нові можливості для аналізу складних медичних зображень та оптимізації діагностичних процесів. Однією з ключових проблем залишається інтерпретація результатів, отриманих за допомогою систем ШІ, зокрема в медичній практиці, де критично важливо забезпечити прозорість і зрозумілість прийнятих рішень. У цій роботі запропоновано метод візуалізації та інтерпретації результатів класифікації серцевих захворювань на основі аналізу МРТ-зображень із використанням моделей глибокого навчання. Основна мета дослідження – пояснити рішення, отримані за допомогою ШІ, у формі, зручній та зрозумілій для лікарів, що сприяє зниженню суб'єктивності у клінічній практиці.

У процесі роботи були розроблені підходи до візуалізації основних груп медичних показників, таких як об'єми серця, викидна фракція, товщина стінок міокарда, а також співвідношення об'ємів і маси. У досліджені описані числові метрики, які застосовуються у медичній практиці. Для представлення ключових медичних показників було виділено 15 показників та об'єднано у відповідні групи. Для забезпечення інтуїтивно зрозумілого подання результатів використано різноманітні форми візуалізації: кругові діаграми для демонстрації співвідношень, 17-сегментна модель міокарда для аналізу товщини стінок, а також числові показники для точного відображення об'ємів і фракції викиду. Такий підхід дозволяє лікарям швидко оцінити структурні зміни серця та зробити обґрунтовані висновки.

Запропонований метод спрямований на підвищення прозорості та довіри до ШІ шляхом забезпечення зрозумілого подання даних, що, у свою чергу, знижує ризики суб'єктивної інтерпретації та когнітивних упереджень. Отримані результати свідчать, що використання таких візуалізацій може значно полегшити процес прийняття клінічних рішень, підвищити точність діагностики та стандартизувати підходи до аналізу медичних даних.

Ключові слова: МРТ серця, патологія серця, глибоке навчання, класифікація, інтерпретація.

Introduction

Artificial intelligence (AI) methods in medical diagnostics enable processing complex medical images, detecting anomalies, and providing preliminary diagnoses, thereby assisting physicians in making informed decisions.[1]. Such technologies can significantly enhance the efficiency of diagnostic processes by reducing reliance on the human factor and ensuring more standardized approaches to data analysis. [2].

The "black box" problem in AI-driven systems is becoming increasingly relevant, especially in fields requiring high accountability, such as medicine, finance, and law. The term "black box" refers to a situation where, although a system can efficiently process input data and deliver results, the decision-making process itself remains opaque to both users and developers. In the case of deep neural networks and other complex AI algorithms, the model's decisions often rely on the interaction of thousands of parameters, making it extremely challenging to trace the reasons behind each outcome. This lack of transparency raises concerns about the accuracy and reliability of AI systems, limits their application, and increases risks associated with incorrect or unfounded conclusions.

However, some approaches aim to address this issue and improve AI system transparency. Developing methods for interpreting and visualizing AI results, such as heatmaps to highlight important areas of an image or visualizing the significance of individual features, allows for a deeper understanding of how the system makes decisions. These tools not only help assess the validity of results but also build user trust in AI, which is particularly critical in high-risk domains.

When discussing the automation of diagnostics and treatment recommendations solely through AI, it is worth noting that, in theory, all physiological parameters and individual characteristics (e.g., body structure, allergies, individual drug reactions) could be accounted for. However, the workload, time, and financial resources required to organize and annotate datasets of such scale are enormous. Moreover, treatment often needs to consider subjective indicators that a physician can only assess during interaction with the patient and through their own perception. For example, evaluating the description of well-being or an individual's pain threshold to determine the appropriate dose of painkillers. In other words, patients with identical diagnoses and physiological parameters may receive different treatments because the physician interprets their well-being differently. In some cases, this approach is entirely justified.

On the other hand, modern medical science aims to reduce the subjective influence on treatment. Physicians may be susceptible to various cognitive biases, such as confirmation bias or recency bias, which can lead to incorrect diagnoses or inappropriate treatments. Unconscious biases, including racial or gender biases, can also affect the quality of medical care provided, resulting in unequal access to healthcare services and varying treatment outcomes for different patient groups [3, 4]. Different physicians may interpret the same clinical data in various ways, further complicating standardization and improving diagnostic accuracy.

Thus, it is essential to balance objective indicators and subjective factors when making medical decisions. Objective data and AI algorithms can reduce the likelihood of biases, ensuring a more standardized approach, while the physician's subjective assessment allows for consideration of unique aspects of the patient's well-being that are difficult to formalize. Such a balance can help optimize the diagnostic and treatment process, making it both accurate and personalized.

This study builds on the authors' previous work, specifically the development of a method for classifying cardiac MRI images using cascaded deep learning models and proposes an explanation method for decision-making that presents the outcomes and features that are understandable to physicians. Our contribution focuses on the analysis, extraction, and visualization of MRI image metrics in alignment with the diagnosis and includes the following:

- Converting medical metrics from qualitative to quantitative forms;
- Presenting the results obtained through deep learning in the form of visual features understandable to physicians.

Recent studies, such as[5], highlight the role of heatmaps and saliency maps in visualizing important image regions that the model focuses on. This enhances physicians' trust in AI and improves the diagnostic accuracy of X-ray and MRI images.

Another study [6] analyzes current advancements in the application of AI for cardiovascular diagnostics and highlights the growing role of technology in improving the accuracy and speed of image analysis, as well as in reducing human errors and radiation exposure, which is critical for MRI. This study emphasizes the importance of implementing models that demonstrate competitive results compared to skilled physicians and underscores the need for further research to explore AI's potential across a wide range of cardiological applications.

Additionally, in publication [7], the authors provided comprehensive guidelines for assessing the "trustworthiness" of AI systems in medical imaging. An important aspect of these guidelines is the recommendations on how to avoid ethical and clinical risks during the development and implementation of AI in the diagnosis of cardiovascular diseases, emphasizing the necessity of compatibility with clinical practice.

The authors of [8] investigate the D-TCAV (Deep Taylor-CAV) method for cardiac image segmentation, which enables a "conceptual" explanation of AI model behavior by identifying key image regions that influence decision-making. The study emphasizes that D-TCAV can identify specific pathological features, such as wall irregularities or differences in chamber sizes, providing physicians with more objective data for diagnostic analysis. This not only automates the diagnostic process but also enhances the transparency and reliability of AI in cardiological studies, reducing the risk of biased or random model decisions. The research demonstrates how such approaches can improve trust in applying AI methods in clinical practice, particularly for high-accuracy cardiac segmentation analysis.

In [9], approaches are described for visualizing the image regions that most significantly influence classification and segmentation outcomes. TorchEsegeta, a platform developed by the authors for interpreting deep learning model decisions in medical imaging analysis, includes metrics for assessing the sensitivity and infidelity of explanations and adapts existing methods for 3D analysis. This was tested on vascular segmentation tasks using TOF-MRA, demonstrating its effectiveness. The authors of [10] proposed a multitask model, MT-BI-RADS, to classify and segment tumors in breast ultrasound images. The model utilizes BI-RADS descriptors to interpret diagnostic decisions, segment tumor regions, and analyze the contribution of each descriptor using Shapley Values. The authors note that the model enhances radiologists' trust in the analysis results, further advancing AI's role in medical diagnostics.

In [11], a method for interpreting deep learning models for single-channel EEG analysis was proposed. The use of interpretable filters and statistical activation analysis enabled the identification of connections between key signals, such as sleep spindles or delta activity, and model predictions for sleep stage classification tasks. The authors of [12] developed the NeuroXAI framework for interpreting deep neural networks in brain tumor classification and segmentation tasks. The platform generates attention visualizations using multiple modern interpretation methods, ensuring model transparency for radiologists. NeuroXAI was applied to MRI analysis focusing on tumor detection and segmentation.

In [13], a deep learning approach was applied to analyse electrohysterographic data for predicting preterm births. The proposed model combines long short-term memory (LSTM) and temporal convolutional networks within an interpretable structure. The authors also introduced a method for interpreting time-series data, enabling clinicians to extract essential information despite limited data availability. The study [14] combined deep learning with semantic web technologies for diagnosing cassava diseases. The model achieved an accuracy of 90.5% and generated comprehensible interpretations for non-expert users, such as farmers. The use of knowledge graphs allowed the integration of contextual information and domain knowledge, significantly improving prediction quality.

In [15], metrics for the quantitative evaluation of model explainability in process monitoring with outcome prediction were proposed. The authors introduced the concept of symbiosis between interpretability and reliability and compared traditional models with post-hoc interpretation methods based on Shapley values. Study [16] evaluated seven saliency methods for interpreting the analysis of chest X-rays. Grad-CAM demonstrated the best results in pathology localization; however, all methods significantly lag behind human performance, particularly in cases involving small or complex-shaped pathologies.

In [17], a novel approach to parameterizing cryo-EM maps using neural networks was presented. The results include precise structural data representations and graph-based interpretations, achieving 99% coverage of amino acid residues for atomic-resolution maps. The research [18] proposed a framework for selecting the most informative features in depression detection models. An analysis of three real datasets revealed that key features include speech pauses, F0 frequency, and eye movements. The proposed approach reduces the number of utilized features while improving classification accuracy.

Thus, modern research confirms that developing explainable AI models and their visualization is critically important for integrating AI into cardiology, enhancing the reliability and accessibility of this technology for clinical diagnosis and patient treatment.

Method for interpreting decisions made by deep learning models

To interpret decisions made by deep learning models, it is necessary to transition from the neural network architecture to features commonly used by physicians to identify heart diseases. Based on the classification of diseases considered in this study, the primary groups of these features can be outlined as follows: ventricular volumes, ejection fraction, volume-to-mass ratio, and myocardial wall thickness and variability.

Group 1: Ventricular Volumes.

One of the critical groups of indicators is heart volumes, which help assess the functioning of the left and right ventricles. The ratio of the left ventricular volume to the right ventricular volume at the end of the systole allows for evaluation of the balance and interaction between the two ventricles during heart contraction. The end-systolic and end-diastolic volumes of the left ventricle help evaluate its contractile ability and the maximum blood volume it can hold before contraction. Similarly, the volumes of the right ventricle assist in detecting potential dysfunctions. For instance, an increased right ventricular end-diastolic volume may indicate abnormal right ventricular, while a reduced left ventricular end-systolic volume may suggest hypertrophic cardiomyopathy [19, 20].

Group 2: Ejection Fraction.

Ejection fraction is another critical group of indicators that measure the efficiency of blood ejection by the left and right ventricles, respectively. These metrics are key for diagnosing conditions such as dilated cardiomyopathy, which often features a reduced ejection fraction. The left ventricular ejection fraction indicates how much blood is ejected from the left ventricle during each contraction relative to its size during filling. Similarly, the right ventricular ejection fraction reflects the pumping efficiency of the right ventricle, which is crucial for diagnosing diseases such as arrhythmogenic right ventricular cardiomyopathy [20].

Group 3: Volume-to-Mass Ratio.

This group includes metrics that reflect the relationship between heart volumes and myocardial mass. The volumes and myocardial mass at different phases of the cardiac cycle help detect pathological changes in the myocardium. For example, an increased myocardial mass relative to the left ventricular volume may indicate hypertrophic changes, whereas a decrease may suggest dilated processes [20, 21].

Group 4: Myocardial Wall Thickness and Variability.

Characteristics determining myocardial wall thickness are also critical for classifying heart diseases. Measurements of myocardial thickness during different phases of the cardiac cycle allow assessment of the uniformity of its contraction and relaxation. For instance, increased myocardial wall thickness during diastole may indicate hypertrophic cardiomyopathy, while decreased thickness may suggest dilated processes. Variability in thickness during contraction and relaxation helps evaluate the consistency and coordination of myocardial contractions. For example, high variability may indicate uneven myocardial contractions, which are characteristic of certain types of cardiomyopathies, such as hypertrophic cardiomyopathy [19].

The core idea of the method, distinguishing it from similar approaches, lies in providing physicians not only with the direct results of pathology identification based on MRI analysis using deep learning models but also with the values of specific metrics (features) that either confirm or refute the results (which is possible even with high classifier performance metrics).

It is worth noting that physicians' identification of the aforementioned features inherently involves a degree of subjectivity. For objective medical diagnostics, it is essential to shift from subjective observations made by physicians to objective numerical indicators that standardize the analysis. For instance, visually identified myocardial wall irregularities, which may indicate pathological changes, can be represented by numerical values, such as the mean standard deviation of myocardial wall thickness at end-systole. This metric objectively reflects the wall thickness variability, reducing the risk of subjective errors and enabling comparison of results between patients.

The implementation of specific numerical metrics for describing medical features ensures greater diagnostic accuracy and reliability, while also creating opportunities for objective evaluation of decisions derived from the application of AI methods.

Moreover, it is important to emphasize that numerical metrics used to represent the aforementioned groups of medical features should preferably align with those already commonly applied for similar purposes. Based on this principle, the study proposes utilizing the following metrics [22]:

1. End-diastolic volume of the left ventricle
2. End-systolic volume of the left ventricle
3. End-systolic volume of the right ventricle
4. End-diastolic volume of the right ventricle
5. Left ventricular ejection fraction
6. Right ventricular ejection fraction
7. Myocardial mass at end-diastole
8. Myocardial mass at end-systole
9. Mean standard deviation of myocardial wall thickness at end-systole
10. Mean standard deviation of myocardial wall thickness at end-diastole
11. Maximum average myocardial wall thickness at end-diastole
12. Maximum average myocardial wall thickness at end-systole
13. Ratio of myocardial mass to left ventricular end-diastolic volume
14. Ratio of myocardial mass to left ventricular end-systolic volume
15. Ratio of left ventricular end-diastolic volume to right ventricular end-diastolic volume

The integration of an MRI image segmentation method within the proposed approach, which significantly improves segmentation accuracy and reduces image artifacts, enables more precise determination of the numerical values of these features.

It is recommended that these features be presented to physicians in both numerical and graphical formats commonly used in medical practice. This dual representation facilitates better understanding and application of the data, improving its utility in clinical settings.

Results and discussion

The main groups of medical features, such as ventricular volumes, ejection fraction, volume-to-mass ratios, myocardial wall thickness, and variability, can be presented as numerical indicators derived from MRI analysis. Each of these features, in turn, is proposed to be presented to physicians using one of the following methods:

- Application of the 17-segment myocardial model for indicators related to myocardial thickness (e.g., maximum average myocardial wall thickness at end-diastole) [23].
- Use of pie charts for visual representation of ratio indicators (e.g., the ratio of left ventricular volume to right ventricular volume).
- Display of numerical indicators (e.g., myocardial volume at end-systole).

Below are the key indicators for each pathology, along with recommended visualization methods, making the results more intuitive and convenient for clinical interpretation:

DCM (Dilated Cardiomyopathy):

- End-diastolic volume of the left ventricle – numerical indicator.
- End-systolic volume of the left ventricle – numerical indicator.
- Left ventricular ejection fraction – numerical indicator.
- Myocardial mass at end-diastole – numerical indicator.
- Ratio of myocardial mass to left ventricular end-diastolic volume – pie chart.
- Maximum average myocardial wall thickness at end-diastole – 17-segment myocardial model.

HCM (Hypertrophic Cardiomyopathy):

- End-systolic volume of the left ventricle – numerical indicator.

- Left ventricular ejection fraction – numerical indicator.
- Ratio of myocardial mass to left ventricular end-systolic volume – pie chart.
- Maximum average myocardial wall thickness at end-diastole – 17-segment myocardial model.
- Mean standard deviation of myocardial wall thickness at end-systole – numerical indicator.
- Standard deviation of average myocardial wall thickness at end-diastole – numerical indicator.

MINF (Myocarditis):

- End-diastolic volume of the left ventricle – numerical indicator.
- Left ventricular ejection fraction – numerical indicator.
- Myocardial mass at end-diastole – numerical indicator.
- Maximum average myocardial wall thickness at end-diastole – 17-segment myocardial model.
- Mean standard deviation of myocardial wall thickness at end-diastole – numerical indicator.

ARV (Abnormal Right Ventricular):

- End-diastolic volume of the right ventricle – numerical indicator.
- Right ventricular ejection fraction – numerical indicator.
- Ratio of left ventricular end-diastolic volume to right ventricular end-diastolic volume – pie chart.
- Maximum average myocardial wall thickness at end-systole – 17-segment myocardial model.
- Mean standard deviation of myocardial wall thickness at end-systole – numerical indicator.

Thus, distinct visualization approaches were developed for each group of indicators (heart volumes, ejection fraction, volume-to-mass ratios, and myocardial wall thickness). Indicators related to ratios are represented as pie charts for visual comparison. Myocardial wall thickness and variability are displayed using the 17-segment myocardial model, allowing data evaluation from a single image without the need for comparing multiple MRI slices. Numerical indicators are used for metrics such as myocardial volume during different cardiac phases, simplifying physician data interpretation.

Examples of classification result interpretation for detected pathology (HCM) are shown in Fig. 1.

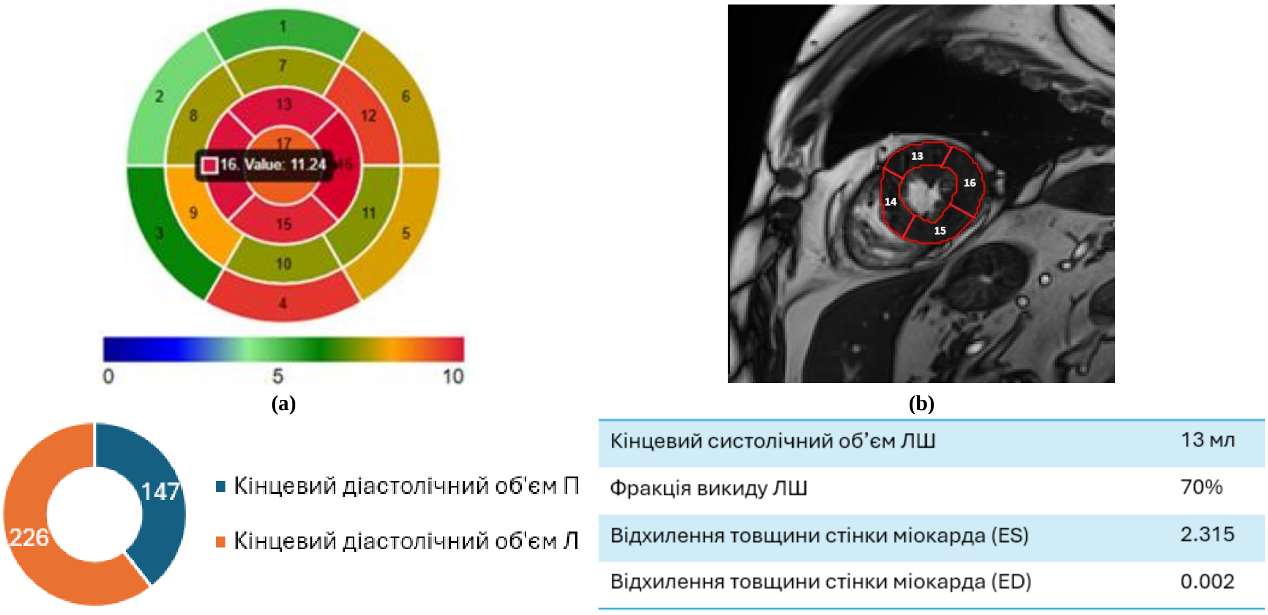

Fig. 2. The types of features representation

As seen above, distinct visualization approaches were applied to each feature related to specific groups (heart volumes, ejection fraction, volume-to-mass ratio, myocardial wall thickness). For ratio features, representation in the form of pie charts was proposed to facilitate visual comparison of indicators. Myocardial wall thickness and variability are depicted using the 17-segment myocardial model, which allows for evaluating these features in a single image without comparing different MRI slices. Numerical values were applied to features such as myocardial volume during various phases of the cardiac cycle, simplifying data interpretation for physicians.

The proposed model for visualization and interpretation enables the presentation of classification results in a format commonly used in medical practice and intuitively understandable for physicians. This form of representation facilitates a clear understanding of the results and helps physicians evaluate decisions made by deep learning models in the context of clinical practice.

Conclusions

The developed method for visualizing and interpreting classification results of heart diseases based on MRI images allows diagnostic indicators to be presented in a form that is accessible and comprehensible for physicians. The obtained results demonstrate that the proposed approaches can significantly simplify the process of analyzing medical data. The use of various visualization approaches for different groups of indicators (pie charts, 17-segment model, numerical metrics) creates the possibility for standardized information presentation, ensuring easy data perception.

Visualizing key indicators helps reduce subjectivity in result interpretation, as the metrics are presented in graphical and numerical forms that are easily understood by medical personnel. The proposed visualization methods can be valuable for supporting clinical decision-making. Physicians can quickly assess structural changes in the heart, aiding in selecting an optimal treatment strategy. The developed methods can be integrated into medical decision-support systems with a simple and intuitive data presentation format, providing a more efficient and objective approach to diagnosing and monitoring cardiovascular diseases.

Thus, the developed method for visualizing and interpreting classification results offers new opportunities for automated analysis of cardiac MRI images, enhancing the accuracy and objectivity of cardiovascular disease diagnostics.

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