A Report on work: Cardiac MRI CBIR for pathologies detection

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Abstract: The early detection of pathologies in the cardiovascular system is very important. One of the most accurate imaging examinations of human tissues is magnetic resonance imaging (MRI), which is a very precise yet non-invasive test. In order to process MRI images to detect pathologies, one of the most promising methods is Content Based Image Retrieval (CBIR). This paper presents a report on the research on that topic as a result of the Miniatura 5 Grant. The main contributions of the paper are: a review of the state-of-the-art methods, a selection of the most promising image features that may be used to identify pathologies, a description of the proposed system for preparing suggestions for doctors, which takes into consideration also methods for presenting the results, which are most often omitted in other researches. The next step will be incorporating full 3D MRI information into the pipeline.

1 INTRODUCTION

Magnetic Resonance Imaging (MRI) is one of the most important tools in medical diagnostics. It is a non-invasive, highly reproducible and accurate method that incorporates the use of a very strong magnetic field which is able to stimulate protons. The physicians are able to change the imaging characteristics by changing its parameters. Moreover, it is possible to obtain images of vessels and arteries using MR Angiography (MRA) (Situ et al., 2019). Cardiac Magnetic Resonance Imaging (CMR) is also able to produce different types of images, including tissue characterization, thrombus and scar capture which provide key information for doctors. Patients are not exposed to ionizing radiation (Peterzan et al., 2016).

There are many heart problems that can be solved by CMR using different settings and imaging types (Salerno and Kramer, 2009; Peterzan et al., 2016). As an example, the presence of coronary artery disease (CAD) (Chang and Kim, 2016), an acute myocardial infarction (AMI) or chronic myocardial infarction (CMI) can be identified with the CMR, which may help in choosing a type of treatment (Peterzan et al., 2016; Tahir et al., 2017). Moreover, CMR is able to capture images for myocardial stress testing (Peterzan et al., 2016) and is helpful in the evaluation of Microvascular Obstruction (Perazzolo Marra et al., 2010). Another example of CMR usage in heart pathology detection may be the detection of Left Ventricular Thrombus using different types of cardiac magnetic resonance imaging (Chaosuwannakit and Makarawate, 2021).

In order to process MRI images to detect pathologies, one of the most promising methods is Content Based Image Retrieval (CBIR), which is currently used in many fields, such as photography, social networks, databases, but also in medicine. There are researches focused on the diagnosis of various types of pathologies, such as diabetic retinopathy (Sivakamasundari and Natarajan, 2015), breast cancer detection (Carvalho et al., 2020) or some cardiovascular pathological changes (Bergamasco et al., 2015b).

This paper presents a report on work on the Miniatura 5 Grant funded by National Science Center Poland, which is dedicated only to preparing initial research on the method for Cardiac MRI CBIR for pathologies detection. The main contributions of the paper are: a review of the state-of-the-art methods related to the topic, a selection of the most promising image features that may be used to identify pathologies and a description of the proposed system for preparing suggestions for doctors. The research also takes into consideration methods for presenting the results, which are most often omitted.

The next stage of the research will be incorporating full 3D MRI image information into the pipeline

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in order to improve the results.

The paper is organized as follows: in the next section there are described methods in medical CBIR. The section 2 contains a presentation of the proposed method. Next, the results of initial experiments are shown. The last section contains a summary and description of future work directions.

2 LITERATURE OVERVIEW

One of the biggest challenges in medical imaging is detecting pathologies with high certainty. This could be very beneficial for choosing appropriate treatment. Due to the recent advances in computer vision and image processing, there are more and more possible usages of computer aided CMR imaging. There is a great area where a lot of tasks are similar to multimedia database retrieval, which in many cases may be formulated as the problem of Content Based Image Retrieval (CBIR) (Münzer et al., 2016).

One of the main challenges in CBIR is proper image segmentation. This is very crucial, especially in medical image processing, because proper separation of, e.g. desired tissues, may highly increase the precision of a later diagnosis suggestion. For segmentation different algorithms are used, e.g. for 2D images a fuzzy connectedness image segmentation with geometric moments (FCISGMs) may be applied (Atique and Bhagat, 2016). Another idea is to use a region growing process with OTSU thresholding (Ramos et al., 2014). There are also methods using U-Net and CNN networks, e.g. (Guo et al., 2020). Another idea is to first localize and then make segmentation of a 3D Cardiac MRI image using a modified version of the 3D U-Net network named 3D DR-UNet (Vesal et al., 2020). As another example of medical image segmentation, a CXR chest image segmentation using a so called CardioNet may be given (Jafar et al., 2022). Sometimes, for CMR image segmentation, there is also used Fully Convolutional Network (FCN) for semantic segmentation (Bai et al., 2018). There are also methods for CRM image acquisition plane recognition using CNN networks (Margeta et al., 2017) or some novel image analysis techniques, like Radiomics, which use information about shape and tissues characteristics as numerical values (Raisi et al., 2020). Additionally, autoencoder approaches for segmentation are also researched (Wibowo et al., 2022), as well as transfer learning usage (Ankenbrand et al., 2021).

Another problem for medical image CBIR is how to retrieve results after segmentation. There are CBIR systems that are universally designed for different types of medical images, like CT, MRI, PET or X-Ray. One of the problems here is the computation time, which can be reduced by dividing an image into a set of blocks (Atique and Bhagat, 2016). There is also an affine transformation used for image alignment along with different metrics (Ayyachamy and Manivannan, 2013). As different features mean, standard deviation, entropy, skewness and energy may be used (Ayyachamy and Manivannan, 2013). For the detection of Interstitial Lung Diseases in CT images, not only the information from images may be used but also from radiology reports with extracting textual information (Ramos et al., 2014). Another method may incorporate information from four types of image projections, like Perfusion and Tagged MRI, LT-SENC, HT-SENC and Cine Images. As feature vectors, information about the dynamic range of the image, Image Spectrum Histograms and Image Gradient Projectors may be used (Wael and Fahmy, 2012).

A huge problem in CMR CBIR is using all 3D depth information stored in the volumetric image. In order to overcome this problem, spectral clustering and as a feature vector the 3D Hough Transform Descriptor (3DHTD) have been proposed (Bergamasco et al., 2015b). Another method for querying for 3D cardiac models is based on the Local Shape Distance Descriptor (LSDD) and a bipartite graphs (Bergamasco et al., 2015a). To summarize, the most often used descriptors for cardiac MRI are shape, texture, motion and clinical-based (Delmondes and Nunes, 2022).

There are also cardiac CBIR systems dedicated to 3D echo images (Doppler images) using dimensions of cardiac ventricles and texture properties, sucha as kurtosis, skewness, edge gradient, color histogram as features (Nandagopalan et al., 2012). There are also methods that decompose medical image features into Discrete Latent Codes using GANs (Kobayashi et al., 2021). For 3D Brain MRI images there are also methods that incorporate dimensionality reduction using so called Loc-VAE (Nishimaki et al., 2022). Another approach for dimensionality reduction may be the 3D convolutional autoencoders (3D-CAE) (Arai et al., 2018). Moreover, there are also SURF, PHOG and VGG16 network based descriptors used to create a one-dimensional vector (Rinaldi and Russo, 2020). For brain images, there are also different features used, like pixel, local and global features that are incorporated together to make one feature vector (Rizvi, 2020). Another example of a deep learning based method may be the usage of Convolutional Siamese Neural Networks for distinguishing between lung cancer and tuberculosis (Zhang et al., 2022). The summary of all the aforementioned methods is shown in Tab. 1.

Most of the research on Medical CBIR does not consider the issue of preparing efficient visualizations for doctors. However, this is a very crucial part of the system because it helps in a faster and more precise understanding of the obtained results. One of the methods that can be used for a medical diagnosis report is a Venn-style diagram (Huang et al., 2020). Especially in cardiac reports, there are used Bull's Eye Plots as well as 2D and 3D maps (Kreiser et al., 2018). There are also some reports where there is a need to annotate uncertainties on images, e.g. using different colors or grayscale areas (Gillmann et al., 2021).

3 PROPOSED CBIR METHOD FOR DIAGNOSTICS

The main goal of the research is to prepare an initial method for efficient and precise providing suggestions for doctors with graphical, easy to understand results presentation. Due to the fact that this task is very complex, as the first stage making a review of the state-of-the-art methods and preparing an initial 2D method was chosen, which has been presented in this paper. The next step will be preparing research on the 3D method.

The proposed system consists of the following logical modules: preprocessing and segmentation, feature extraction, the CBIR suggestion module and visualization module. All of the modules are described in more detail in the following subsections.

3.1 Preprocessing and Segmentation

In Computer Vision and Image Processing one of the most important steps is the proper preparation of the image for further processing and analysis. One of the types of segmentation that has been considered is neural network based. For such an approach, the U-Net architecture has been chosen, which is one of the most efficient image segmentation methods in medical imaging (Siddique et al., 2021),(Tong et al., 2018). Additionally for higher performance, it can be supported by other network architectures like R-CNN (Xu et al., 2018).

One of the problems that may occur during U-Net usage is the complexity of the input data. In order to reduce it but also to leave different pixel values in tissues, the Mean shift segmentation has been proposed as an initial image preprocessing step before using it as an input for the U-Net. The idea of heart extraction and example result is shown in Fig. 1.

During the research, we also noticed the problem of image alignment and registration. Images captured during acquisition may have different orientations and scalings. For more precise work with different algorithms from the pipeline, there may be at least some rotation needed. There are many researches dedicated to image registration using more classical approaches (Hill et al., 2001) or Deep Learning (Fu et al., 2020). During this initial research, that topic was not taken into consideration and was left for further development - all images were rotated manually by a human.

Another idea that has been considered during the research is the MRI image type detection. It has been proved that such an additional step can improve the overall precision of obtained results (Wael and Fahmy, 2012), thus it was added to the pipeline. A pre-trained CNN neural network is used in order to detect image type, which may be e.g. a cine-SSFP or TSE image. This step is important because it helps to separate the pipeline for more precise training models for heart extraction from an MRI image.

3.2 Features Extraction

Extracting features from the image is one of the most crucial parts of Content Based Image Retrieval systems. Choosing proper features may greatly improve the precision of returned results. After analysis of the aforementioned state-of-the-art methods, described in Section 2, the most promising ones were chosen.

Statistical and global features are able to represent information about some features that describes the image globally like the mean pixel value or the characteristic of the image histogram. Additionally, with e.g. Gabor filters, they are able to compare different textures present in images (Barbu, 2009). Global features are commonly and successfully used in CBIR methods (Varish and Pal, 2015).

Another types of features which are very promising are heart-based. Some diseases are characterized by e.g. overgrowth of one of the cardiac ventricles and such information may be crucial for precise diagnosis. Due to that fact, we propose to use two types of features: proportions of heart width and height and proportions of heart ventricles. There are some algorithms for automatic heart ventricles segmentation (Peng et al., 2016) and measurement (Wang et al., 2019). Extracting these features automatically from images will be researched in the future and at this stage has been done manually.

It has been proven that Scale-Invariant Feature Transform (SIFT), Orientated FAST and Robust BRIEF (ORB) or Speeded Up Robust Feature (SURF) descriptors are able to provide precise results for CBIR (Chhabra et al., 2020). Due to that fact, they are also promising for their usage in the medical CBIR.

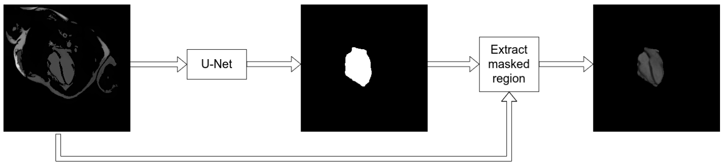

Figure 1: Heart mask generation and extraction from the MRI image. Images represent actual trained U-Net results. Original MRI image source: (Campello et al., 2021)

The last type of considered feature descriptors are neural network-based descriptors. Recently Deep Learning methods are becoming more and more popular in many areas, including Content Based Image Retrieval systems (Staszewski et al., 2021; Rinaldi and Russo, 2020). For extracting deep features, most often VGG-16 and VGG-19 are used.

Choosing proper descriptors is not the only problem in feature extraction. Another crucial thing is the selection of the area of the image from which these features should be extracted. During the initial research, it was discovered that higher precision could be obtained using an extracted heart image. Moreover, because the neighboring area to the extracted heart may contain some important data for image processing and classification, we propose to use them together with the heart features, creating a "ring" around the extracted heart.

3.3 Making Recommendations for Doctors

Preparing recommendations for doctors is a very complex task. When CBIR is used, one of the main problems is: storing features together with images and querying the database in an efficient way (Deniziak and Michno, 2019). In this research, we focused only on the querying part, with a simple database structure based on a vector. A more thorough investigation on how to efficiently store information about images will be done in future research.

The CBIR suggestions module works as follows: firstly, as an input retrieve MRI type and feature vector. Next, all images of the same MRI type are selected. After that, for each image and feature set $s \in (heart, ring)$:
a) find the L2 norm distance between input feature vector $|a|$ and feature vector of the image from database $|b|$ using following equation:

$$dist_s(|a|,|b|) = \sqrt{\sum_{k=0}^{n} a_i - {b_i}^2}, \quad (1)$$

b) compute the total distance:

$$val_a = 0.75 \cdot dist_{heart}(|a|,|b|) \quad (2)$$

$$val_b = 0.25 \cdot dist_{ring}(|a|,|b|) \quad (3)$$

$$dist(|a|,|b|) = val_a + val_b, \quad (4)$$

c) store id of the image from database together with total distance.
Next all stored distances are sorted and top 5 of them are selected and returned as a main disease suggestion.

The metadata connected with the images contains the main cardiac disease and a list of other problems that a patient may have, like thick adipose tissue or a past myocardial infarction.

What was not covered by most of the researches is data visualization for doctors. This is done by the last system's module, Visualization Module, which as an input receives data about the five most similar images together with their metadata.

The module generates charts that contains recommendation for doctors. Because some diagrams may show information more clearly, three types of charts are generated: pie chart, words cloud, bar chart.

The idea of showing more than one diagram is to choose the most efficient one after consultations with different doctors, which should be covered in future research. During the research it occurred that it may be helpful to not only show suggestions about the main disease that is present on the MRI image, but also some additional information that may be connected to the patient. Thus, there are generated two sets of charts: one containing the main disease and the other showing all stored additional information.

4 INITIAL EXPERIMENTS

Due to the main idea of the Miniatura 5 grant, which is gathering knowledge and performing some initial research that is designated to be highly extended by future research, more theoretical considerations have been made and only initial experiments have been performed using the dataset (Campello et al., 2021).

One set of tests was dedicated to checking which type of segmentation would be most suitable for initially preprocessing the image in order to make the heart more significant than the background and other tissues. For initial preprocessing, the following segmentation algorithms have been considered: K-Means, DBSCAN, OTSU, Mean shift, Watershed (with OTSU thresholding applied before to the image), U-Net. The example segmentation results for the unsupervised methods are shown in Fig. 2. As can be seen, each algorithm, except DBSCAN, was able to segment the heart from other tissues. Another type of test was made in order to check the U-Net based segmentation, which proved the high efficiency of that method.

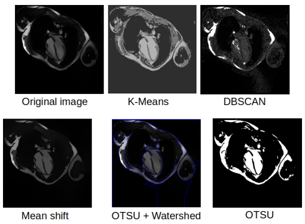

Figure 2: The results of different segmentation algorithms. Original MRI image source: (Campello et al., 2021)

In order to test the idea of MRI image type detection, a CNN neural network has been implemented using Python and Keras library. Cine and LV images from (Campello et al., 2021) has been chosen for training and testing the network. The average precision for LV images was 0.87 and for Cine images was 0.83. This results should be improved by tuning the parameters and architecture of the network.

Another experiments were made in order to initially test module for generating suggestions for doctors. As features mean, variance, median, kurtosis, skewness has been chosen. During the tests, it has been seen that the variance values are not able to be used for differentiating classes of images on its own. The results for kurtosis were much better, but for Congenital Arrhythmogenesis class the differences were still high. This should be investigated more during future research together with using Gabor filters.

The next tests were performed to create suggestions using CBIR. Four types of queries have been made in order to check if the system proposes the correct disease. For the Hypertrophic Cardiomyopathy, Tetralogy of Fallot and Dilated Left Ventricle the system proposed correct suggestions. The problematic one was Calcaneal insufficiency avulsion, where the system was not certain about the disease and proposed all classes with the same probability. This may be the result of an insufficient number of features - as a further research direction it should be investigated which ones should be the most suitable.

The last set of experiments has been made to test the correction of chart generation. For that purpose, the Matplotlib was used to generate bar and pie charts and WordCloud for generating word clouds. The module was tested to see if it generates correct charts for specified data - for each query it was successful.

5 CONCLUSIONS

In this paper, a report on work on Cardiac MRI CBIR Retrieval for pathology detection has been presented. During the research, a review of different methods that are applied to medical CBIR has been made. Next, all of them were analyzed for used segmentation, features and metrics for comparisons. Additionally, an initial method for CBIR has been proposed that includes: a selection of the most promising image features that can be extracted from MRI images with the proposition of using the closest heart's neighboring pixels, a description of the comparison and suggestion method together with results visualization and an overview of the architecture of the proposed system.

Moreover, some initial experiments were performed in order to check the main assumptions of the proposed method. The results showed that for image segmentation and heart extraction, the U-Net based method should be sufficient. However, the feature set should be investigated more thoughtfully in order to find the features that have the best performance when comparing images connected to different diseases.

When analyzing existing methods and working on the research, there appeared many further directions and ideas. Not only improving the performance of the feature set should be made, but also some efficient metrics for comparing them during CBIR comparison phase. More work should also be done in order to check if an additional feature set for the heart's neighboring area may improve the precision of suggestions or not. Another way of improving the results may be by adding information extracted from e.g. ECG analysis or patient information, like e.g. age. Moreover, because at this stage only 2D images were used, another future research direction will be using whole 3D MRI image data together with the time series.

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Table 1: Comparison of chosen CBIR methods

Research	Supported images	Algorithms/Methods	Metrics
(Atique and Bhagat, 2016)	2D: general CT, MRI, PET, X-Ray	*segmentation:* CISGMs, *features/image retrieval:* LEBIR, *additional:* dividing an image into blocks	no strict information
(Nandagopalan et al., 2012)	2D: cardiac Doppler image, (echocardiography)	*segmentation:* FKM-SQL algorithm *features/image retrieval:* dimensions of cardiac ventricles, texture properties, kurtosis, skewness, edge gradient, color histogram, etc.	Euclidean distance
(Ayyachamy and Manivannan, 2013)	2D: brain, chest, liver, limbs CT, MRI, PET, X-Ray, US	*segmentation:* no information *registration:* aligning images using affine transformation *features/image retrieval:* sum of squared distance, mutual information 7 metrics tested	Euclidean, Manhattan, Mahalanobis, Canberra, Bray-curtis, Squared chord, chi-squared distances
(Wael and Fahmy, 2012)	2D: cardiac MRI	*segmentation:* no information *features/image retrieval:* Dynamic Range, Image Spectrum Histogram, Image Gradient Projectors *additional:* detecting the image type (Cine images, LT-SENC, HT-SENC, Tagged MRI and Perfusion MRI)	Euclidean distance
(Ramos et al., 2014)	3D: interstitial lung diseases CT	*segmentation:* region growing process + OTSU, extracting VOIs *features/image retrieval:* text distance calculation, local mean, standard deviation, skew, kurtosis *additional:* supporting CBIR with information from text reports	Euclidean distance
(Bergamasco et al., 2015b)	3D: cardiac MRI	*segmentation:* Seg3D + ImageVis3D software *features/image retrieval:* 3DHTD used to extract features *additional:* method compares 3D models, Spectral clustering is used	Euclidean distance
(Bergamasco et al., 2015a)	3D: cardiac MRI	*segmentation:* Seg3D + ImageVis3D software *features/image retrieval:* LSDD *additional:* a bipartite graph is constructed form two 3D models	Euclidean and Manhattan distances
(Kobayashi et al., 2021)	2D: glioma/brain MRI	*segmentation:* segmentation decoder *features/image retrieval:* autoencoder, decomposing into normal and abnormal anatomy codes *additional:* semantic components decomposition	Euclidean distance
(Nishimaki et al., 2022)	3D: brain MRI	*segmentation and features/image retrieval:* localized variational autoencoder (Loc-VAE) *additional:* dimensionality reduction method	not applicable
(Rinaldi and Russo, 2020)	2D: general MRI, X-Ray, TAC	*segmentation:* no information *features/image retrieval:* descriptors: SURF, PHOG, VGG16-based	cosine distance
(Rizvi, 2020)	2D: brain MRI	*segmentation:* no strict information *features/image retrieval:* pixel, local and global features	no information
(Arai et al., 2018)	3D: brain MRI	*segmentation and features/image retrieval:* 3D convolutional autoencoder *additional:* dimensionality reduction method	not applicable
(Zhang et al., 2022)	2D: lungs CT	*segmentation and features/image retrieval:* CSNN	L2 norm distance