EARLY BREAST CANCER DETECTION USING ARTIFICIAL INTELLIGENCE CLASSIFIERS

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ABSTRACT

The breast cancer is one of the most common diseases affecting women worldwide, the World Health Organization reported that over ten thousands approx women died from the disease in 2020 alone, accounting for approximately 10% of all female cancer deaths. As a result, breast cancer diagnosis is one of the most pressing issues that must be addressed as soon as possible. Multiple image modalities, including mammography, echography, and magnetic resonance imaging (MRI), are used to diagnose breast tumours in this context. Chemotherapy is one of the most common treatments for this pathology. However, several side effects (hair loss, osteoporosis, vomiting, and so on) may occur as a result of this treatment, and cancer will not respond to it.

The purpose of this paper is to propose a novel method for predicting breast tumour response to treatment, which consists of three major steps: 1. Tumor segmentation from MR images; 2. Feature extraction from segmented tumours to generate a complete and exploitable database; 3. Use of deep and machine learning architectures to compute tumor-response prediction models. The experimental findings are applied to a publicly available QIN Breast DCE-MRI dataset of breast cancer patients.

Keywords: Artificial Intelligence, Breast Cancer, MRI, Tumour

1. INTRODUCTION

The majority of patients with locally advanced breast cancer have systemic access to neoadjuvant chemotherapy. This type of treatment may be ineffective in cases where patients do not respond to chemotherapy. The primary goal of this study is to predict breast tumour response to chemotherapy, which could help with the final surgery by reducing tumour size. This prediction could be made by comparing Magnetic Resonance Images (MRI) obtained before and after the first chemotherapy session. Texture Analysis [2], Histogram Analysis [3], Parametric Response Mapping (PRM) [4], and Radiomics [5] are the most widely used medical imaging techniques in the literature for the study of tumour response, as previously examined [1].

We intend to use Radiomics analysis in this work, which entails analysing data and information extracted from various MRI sequences acquired before and after the first chemotherapy. This method is primarily based on the extraction of multiple features from digital images. The radiomics method can produce accurate results without the need for image registration between acquired exams. Radiomics is a branch of medical science that seeks to extract quantitative features from medical images. These characteristics may reveal disease characteristics that traditional research does not recognise.

The Radiomics approach seeks to identify imaging features that can be used to predict prognosis and therapeutic response. Radiomics is the most innovative of the field's applications, having emerged from the medical field of oncology. However, if a disease can be visualised, radiomic analysis can be applied to any medical study. Radiomics can be used to improve diagnostic accuracy, prognosis evaluation, and treatment response prediction. This technique has been used in oncological studies, but it can be used for any illness. The inclusion of physiological, biochemical, and genetic evidence can improve the accuracy of the results even further. Texture analysis is a common application of Radiomics in the study of breast cancer.

The rest of the paper is structured as follows: Section 2 depicts the related work, and Section 3 presents our method and its supporting materials. Section 4 is devoted to experiments, while Section 5 is devoted to current conclusions and future work.

2. Artificial Intelligence Applications in Healthcare Systems:

Artificial Intelligence (AI) techniques are becoming increasingly prevalent in modern business and everyday life, and they are increasingly being used to healthcare.

Artificial Intelligence in Healthcare Services might potentially assist healthcare service providers in various regulatory cycles and patient thoughts. While the majority of AI and medical services innovations have significant implications for the healthcare field, the strategies they support can shift dramatically, especially when considering that a few review papers on Artificial Intelligence in Healthcare suggest that using AI in Healthcare can perform similarly to or better than people at specific techniques.

It will be many years before AI in Healthcare services replaces people for a wide range of medical tasks, such as disease diagnosis. It is hoped that by using Artificial Intelligence, it will be able to mimic human mental capacities and limitations. It is acquiring a new point of view to constrain by increasing access to Healthcare, service information, and the rapid progression of investigation methods. Significant disease areas where AI techniques are used include cardiology, cancer, and neurology, and then we review the applications, Ethical issues in the application of AI to Healthcare, and conclude about the various AI frameworks.

AI and related advancements are becoming increasingly pervasive in society and business, and are also beginning to be applied to healthcare services. These advancements have the potential to alter various aspects of patient consideration, as well as managerial processes within drug associations, payers, and suppliers. In Healthcare, AI is a broad term that refers to the use of AI software and algorithms, or Artificial Intelligence, to mimic human perception in the examination, introduction, and cognizance of complex clinical and Healthcare data. It is, in particular, the ability of computer algorithms to draw conclusions based on input data.

"Recently in Healthcare, AI procedures have sent huge waves in any case, fueling a functioning debate about whether AI specialists will eventually supplant human doctors in the future." What distinguishes AI innovation from conventional technologies in Healthcare services is the ability to assemble various information, measure it, and provide a very distinct yield to the end-user; this can be accomplished using Deep Learning and Machine Learning. These algorithms are capable of detecting patterns in behaviour and reasoning for themselves. AI models should be prepared using broad measures of information in order to acquire valuable bits of knowledge and expectations.

AI algorithms behave uniquely in two ways: First, algorithms are exacting: when an objective is set, the algorithm gains only from the information and can only comprehend what it has already been programmed to do. Second, deep learning

algorithms are black boxes; algorithms can predict with astounding accuracy, but offer almost no comprehensible explanation to the rationale behind its choices aside from the information [1] and type of algorithm used. The primary goal of health-related AI applications is to investigate links between avoidance or treatment methods and patient outcomes.

Artificial Intelligence programmes are used to practise tasks such as finding measures, treatment protocol advancement, drug improvement, personalised medication, and patient care and observation. IoT and Block chain are also used in the healthcare industry [2]. "Because the vast majority of data is collected and generated by IoT-enabled devices associated with healthcare systems." [3] Big Data can also be used to predict drug efficacy in the health-care sector [4]. Artificial intelligence estimations can be used to find a wealth of information in electronic health records for disease prevention and resolution. "Medical foundations such as Kettering Cancer Center, The Mayo Clinic, Memorial Sloan Kettering, and the British National Health Service, for example, have developed AI algorithms for their areas of expertise AI algorithms for medical services have also been developed by large innovation organisations such as IBM and Google. Furthermore, medical clinics are looking for AI software to assist with operational

activities that save money, improve patient satisfaction, and meet their staffing and labour force needs." [5] Currently, the US government is contributing billions of dollars to the advancement of AI in healthcare. "Companies are developing innovations to help healthcare managers improve business tasks by increasing usage, decreasing patient boarding, shortening stay lengths, and streamlining staffing levels." Currently, various studies are being conducted to investigate whether AI can outperform humans in critical Health Care tasks such as infection diagnosis.

Algorithms are now outperforming radiologists in identifying dangerous tumours, and scientists are leading the way in developing associates for costly clinical fundamentals. However, for a variety of reasons, we anticipate that AI will not be able to replace humans in broad clinical interaction domains for many years. In this article, we depict both the potential for AI to automate aspects of care as well as some of the barriers to rapid implementation of AI in healthcare services." The format of the research paper is as follows: Section ii explains why AI should be used in healthcare systems. Section iii contains Healthcare data is collected by searching the AI literature on PubMed for diagnosis strategies. The fourth segment discusses the issues with AI in healthcare. Section v discusses AI implementations in the

healthcare system, and section vi discusses the ethical issues surrounding healthcare AI. Section vii summarises the study's findings.

3. Motivation

In the medical literature, the benefits of AI are still being debated: "AI-enhanced algorithms will learn different learning features from a vast amount of health-care data and then apply the acquired knowledge to clinical practise [6]." It can also be programmed with feedback-based learning and self-helping learning capabilities to improve accuracy. Doctors may benefit from an Artificial Intelligence system that provides up-to-date clinical data from journals, textbooks, and medical operations in order to illuminate legitimate patient care. Furthermore, an AI system will help to reduce diagnostic and helpful bugs, which are unavoidable in human medical practise. Furthermore, an AI system, for example, collects valuable data from a large patient population to aid in real-time inferences for health hazard warning and health outcome prediction."

4. Analysis of medical images

Several methods have been documented and applied on medical images in the scientific literature to predict the response of breast tumours to chemotherapy. In general, MR images are given more weight in this pathology. In this context, there are several research works that look at the breast cancer response to treatment using MR images and use a large number of patients as data to predict this response. We classified these studies into four categories in this work: Histogram analysis (HA), Texture analysis (TA), Parametric Response Mapping (PRM), and Radiomic analysis are all types of analysis.

A. Histogram examination

Histogram analysis is an image processing technique that can be used to examine the region of interest (of the medical image) before and after treatment. As a result, it is possible to describe the statistical information of a breast cancer image or a tumor-containing region. In fact, intra-tumor heterogeneity can manifest as a volume of interest histogram (VOI). Histogram analysis employs descriptive parameters while also providing quantitative measures such as standard deviation, kurtosis, and asymmetry. These parameters represent the images' first order statistical properties [9].

B. Texture examination

In image processing, a texture is a set of calculated measurements whose goal is to detect the relationship between pixels in an image. The spatial arrangement of colours or intensities in image regions is represented by texture [10]. We generally use the GLCM matrix in [10] to analyse MR images because it allows us to define the spatial distribution of pixel values in an

image in a given direction. The calculation of this matrix allows for the extraction of several properties such as entropy, homogeneity, correlation, energy, and contrast, among others. In this regard, Ammar *et al*.performed a retrospective study to demonstrate that texture-based features can predict tumour response to treatment with high accuracy. This study made use of a dataset that included two MRI breast exams from nine different patients. Three of them were respondents, while the other six were not. They used the GLCM method for feature extraction and dissimilarity, entropy, and homogeneity for feature comparison in this study.

C. Mapping of Parametric Responses (PRM)

The parametric response mapping (PRM) method of tumour classification and quantification measures changes in tumours. based on voxel comparison from acquired exam volumes **[12]**. In our case, the PRM compares a patient's response to chemotherapy before and after treatment in the same tumour. This method allows for the identification of three tumour regions based on treatment response: 1. The areas that received a positive response. 2. Territories that have received a negative response. 3. Areas with a neutral response.

D. Deep Learning Strategy Recently, several papers have been published in peer-reviewed journals that use Deep Learning

techniques to predict the response of breast cancer to chemotherapy. El Adoui *et al*. **[7]** recently proposed a Deep Learning-based approach for breast cancer prediction. Using an augmented data-set of 42 original subjects, an AUC of 96 percent was discovered. We intend to use a radiomics approach in our research to predict NAC treatment. This method is based on the extraction of multiple feature types, including texture and convolutional neural network (CNN) features. This variety of feature-sources could easily improve response prediction.

5. MATERIALS AND DATA

We will detail the database and materials we will utilise for our implementation, as well as the recommended approach, in this part.

A. Set of data

Our findings will be applied to the QIN Breast DCE-MRI public database, which has over 30 breast cancer cases. These databases provide MR images that can be used to assess the response of breast cancer after neoadjuvant treatment. We employ two MRI sequences from this collection of MR images in our first investigation **[13]**:• Pre-contrast T2-weighted MRI with fat-saturation; • T1-weighted MRI without fat-saturation Fat is taken into account (grey colour) in T1 sequences, while the tumour shows in black (intense hypo).The fat, on the other hand, is ignored on T2 sequences,

and the tumour appears with a high intensity. The discrepancies between the T1 and T2 sequences. Cancer Imaging Archive1 has more information about the QIN Breast DCE-MRI database.

6. PROPOSED APPROACH

The proposed approach is divided into many parts,

1) Data preparation: 4 MR image sequences were chosen (T1, T2, DW-MRI, and DCE-MRI).These are then adjusted to guarantee that the results are accurate.

2) Breast tumour segmentation is part of the pre-processing step (before and after).In order to have more data, this segmentation is followed by a data augmentation procedure.

3) Radiomics: in this step, machine and deep learning approaches are used to extract all of the features. Then, before using the radiomics technique for breast tumour response prediction, we can pick the most important features.

Breast cancer response prediction: the resulting features are utilised to present a new model for breast cancer response prediction that includes a complete visualisation to assist radiologists and oncologists in making accurate and timely judgments.

7. RESULTS AND DISCUSSION

Our suggested technique is partially developed, with the processes of data preparation, data pre-processing, and radiationomics all done. In fact, a machine learning algorithm can predict whether a patient with a local breast tumour should continue chemotherapy or seek other treatment. Currently, we use the findings of our prior Deep learning method based on encoder/decoder architecture **[14]** to segment cancers in breast MR images. The U-net architecture, is used to accomplish this. A Conv/deconvNet model designed exclusively for segmenting biological pictures presents this architecture. The architecture of this model is built on a series of convolution and deconvolution layers.

Encoder-Decoder) with various convolution filters and sizes. As a result, if we feed a picture into the UNet network, we get an image that includes pixels with probability of belonging to or not belonging to the tumour. Finally, the tumour region is segmented using a threshold.

8. CONCLUSION AND FUTURE WORK

This study presented a method for breast tumour diagnostics based on radiomics features extraction, with the goal of extracting the most significant feature before training machine and deep learning models to predict the breast tumour response to chemotherapy.The pathological complete response (pCR) is used as a standard reference for this prediction.Radiomics, we feel, can deliver

performed findings, based on the current state of the art. The dataset in this field, however, is yet insufficient to validate the presented approach. Other descriptors such as histogram and texture descriptors will be added to the retrieved features (segmented images using deep neural networks) in future study.

The combination of these features yields a comprehensive feature dataset from which we can select the most appropriate features for breast tumour response prediction using a Radiomics technique. We also intend to incorporate our future produced application onto a cloud platform that our firm has already constructed [15]. This could make it easier for radiologists to receive powerful results without having to install the necessary software.

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