Breast Cancer Medical Imaging Multimodality Lesion Contours Annotating Method

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Invention Proposal

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Abstract

A method and process using a system for providing a User Interface (UI) to annotate and visualize masses and calcifications of breast cancer lesions in a *Multimodality* strategy are disclosed. The *Multimodality* strategy supports the following image modalities: (i) MammoGraphy (MG) in both CranioCaudal (CC) and MedioLateral Oblique (MLO) views; (ii) UltraSound (US); and (iii) Magnetic Resonance Imaging (MRI) volumes. The interface receives a set of medical images to be annotated. In order to annotate the medical images, the UI comprises two lesion tools: (1) a free-hand polygon tool for annotating the masses of breast cancer lesions; and (2) a bullet probe on the image for annotating the calcifications of breast cancer lesions. These tools generate a dataset of manual annotations, which will be able to extract features (e.g., lesion contours, intersections, and shapes) that can be used in the lesion segmentation and classification computation made by automatic agents. Such automatic agents can have the integration of algorithms from Artificial Intelligence (AI), Machine Learning (ML) or Deep Learning (DL) literature.

1 Introduction

Medical imaging diagnosis [16] is a routine effort performed by radiologists to help diagnose or monitor a medical condition [29, 59, 69]. Medical imaging diagnosis allows doctors to identify pathologies by decoding the characteristics of tissues through the examination of features in medical images [3, 78]. It plays a central role in modern medicine in particular for cancer prevention and diagnosis, which is one of the major causes of mortality worldwide [48]. However, proper classification, localization, detection, segmentation, and registration of tumours requires the use of different image modalities which contribute to the reliability of the diagnosis [63]. In our work, we focus on the challenges of supporting *Multimodality*[1] in medical imaging diagnosis applied to the domain of breast screening. Breast cancer is the most common cancer in women worldwide, with nearly 1.7 million new cases diagnosed in 2012, representing 12% of new cancers and 25% of all 166 cancers in women [31].

Breast screening plays a fundamental role in the reduction of patient mortality rate [15, 19, 20]. Early diagnosis of asymptomatic patients allows for early intervention and treatment, significantly increasing the survival rate for breast cancer patients. The most widely employed image modality for population-based breast screening is MammoGraphy (MG) [41]. However, high-risk or dense breast patients require UltraSound (US) or Magnetic Resonance Imaging (MRI) volumes for proper examination [9, 52]. Therefore, it is quite rare to conduct screening or diagnosis using just one modality. The most common breast screening workflow involves several imaging modalities, including MG, in both CranioCaudal (CC) and MedioLateral Oblique (MLO) views, US, and MRI volumes [74]. The rates and costs of visualizing several modalities separately (*i.e.*, one modality each) have an inherent risk of less patient care and the increase of costs associated with unnecessary additional exams.

Deep Learning (DL) algorithms have increased the quality of automatic medical diagnosis at the cost of building *datasets* [37] to train and test such supervised Machine Learning (ML) methods [3]. In the radiology room, medical imaging annotations [8, 10] are one of the main activities of radiologists and the quality of annotation depends on the clinician experience, as well as on the number of studied cases [38]. Manual annotations [18] are very useful to extract features like contours, intersections, margins, and shapes that can be used in the processes of lesion segmentation (*i.e.*, masses and calcifications) and classification (*i.e.*, BIRADS [17]) made by automatic (*AI-Assisted*) agents [79]. In this document, we propose a new method and process that generate a standardized [42, 54] *dataset* of medical imaging annotations, across the domain of breast cancer, adopting a *Multimodality*[1] strategy (*i.e.*, MG, US and MRI) in order to provide clinicians a tool for the production of qualified *datasets*. Also, we foster clinicians' sharing and collaborative evaluation by developing a distributed, remote accessible.

[1] *Multimodality*: diagnostic technique for the patient treatment via: (1) MG, both CC and MLO views; (2) US; (3) MRI; and (4) text. The considered text modalities are, for instance, report information, personal history, family history, age, among others.

2 Background

Relevant for the technological and commercial *due diligence*, in this section we identify competing technologies (Table 1) and explain the advantages and disadvantages of each. Our approach covers the limitations of the works following described. More specifically, we are able to deal with non-homogeneous data. Comprising multimodal images, classification (*i.e.*, BIRADS score) and annotations (*i.e.*, delineation of the lesion contours). To ascertain the usefulness of such non-homogeneous and multimodal source of data, we aim to provide a novel solution for the lesion delineation (Section 5.2.1).

2.1 Clinical Domain

AI-Assisted interfaces already showed breakthroughs in the clinical domain (or in our case, the breast cancer diagnosis), through high quality data (*i.e.*, the BIRADS classification provided by DL methods) with annotations (Section 5.2.2). The main idea behind our work is to build a CNN for each modality (*i.e.*, CNN channel), and then to perform a "deep fusion" over the different channels [44, 75]. This will allow us to use the learned high-level features of all channels. Such channels are the patterns on lesion masses (Figure 1) and calcifications (Figure 2). The training is supervised, or semi-supervised [57, 82, 83], meaning that the deep architecture will need the *ground-truth* (annotations and BIRADS classification) obtained via the support of a *Multimodality* strategy [33, 68]. Therefore, the support for multi-modal UIs [28, 76] is fundamental in the development of such invention. This will also enable radiologists to intervene in the workflow, whenever a new image is added to the network. In addition, the concept of "*aging the net*" [67] is also reachable, meaning that a CNN architecture can be fully supervised, trained as more examples are ready to be fed to the network.

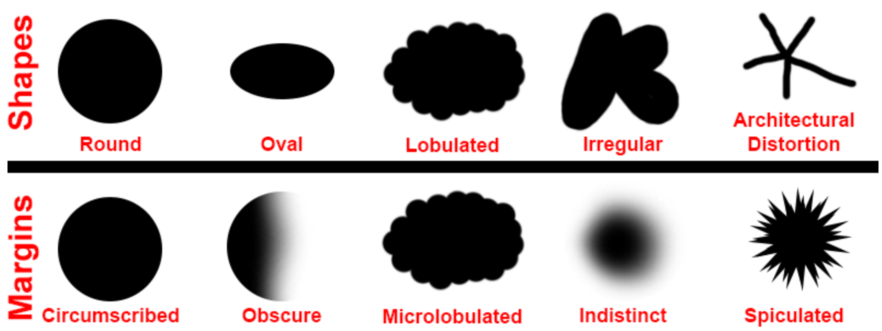

Figure 1: Lesions Types [49] - First line is shown the type of Shapes: **Round**, **Oval**, **Lobulated**, **Irregular**, and **Architectural Distortion**. The second line shows the type of Margins of the lesion: **Circumcribed**, **Obscure**, **Microlobulated**, **Indistinct**, and **Spiculated**.

First of all, we need to know the type of lesion shapes, calcification shapes, and size to understand how clinicians classify them. Regarding the lesion typification (Figure 1), we have a twofold of characteristics: (i) *benign*; and (ii) *malign* masses. On one hand, the *benign* masses are either **Round**, **Oval**, or **Lobular** shapes. On the other hand, the *malign* masses are either **Lobular**, **Irregular**, or has **Architectural Distortion** shapes. The margins can also tell us information about the lesion. There are five types of margins, described as follows. The (1) **Circumscribed** is benign. The (2) **Microlobulated**, (3) **Indistinct**, and (4) **Spiculated** are suspicious findings, with the last one being the most suspicious. Finally, we have the (5) **Obscured** margin. In this case, part of the margin is hidden by fibroglandular tissue. If a patient get an obscured margin result, the suggested action [41, 52] is to perform an US.

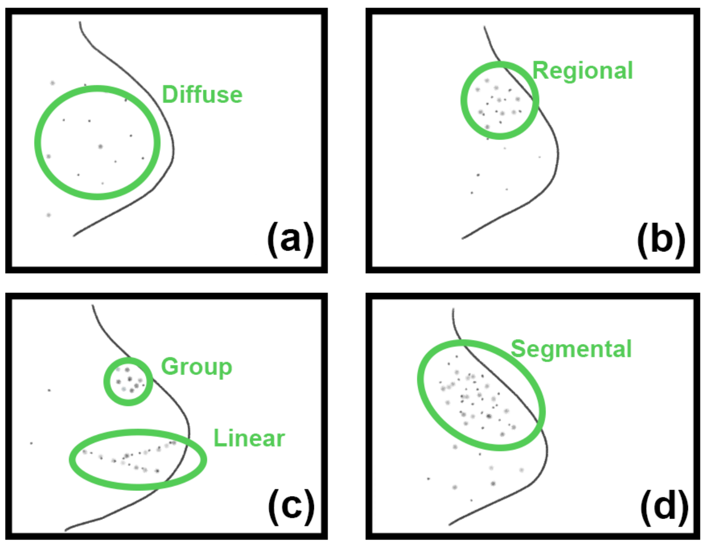

Figure 2: Calcification Type [50] - The **Diffuse** is when the calcifications are "randomly" spread. The **Regional** is when the calcifications are close to each other forming a sort of a "circle". The **Group** is a small area with few calcifications. The **Linear** is when the calcifications form "lines". The **Segmental** is similar to the Regional but approaching a more oval shape instead of a circular.

Regarding the typification of calcifications (Figure 2), we have five types. The **Diffuse** case means that calcifications are dispersed randomly throughout the breast. Secondly, the **Regional**, when several calcifications are occupying over two centimeters of the breast. Next, the **Group** is a small amount of calcifications in a small area of the breast. The **Linear**, that forms a line, may mean that the calcifications are deposited in a duct [41]. Lastly the **Segmental**. This probably means that the calcifications are deposited in the duct or ducts, and their branches [41].

In the context of breast cancer, the requirements for *Multimodality* have a significant impact on the clinical workflow. Although MG is the primary imaging modality for breast screening, it may be insufficient to reach a correct and complete *dataset* generation for the automatic agents and autonomous diagnostic purposes. Therefore support for visualization of multi-modal images and with associated *dataset* of annotations can provide improvements and insights in the breast screening radiology workflow. With this document, our goal is to propose a novel method and tool for the medical annotation of these lesion masses (Figure 1) and calcifications (Figure 2). From the interaction between clinicians and this tool, a standardized *dataset* is generate. Latter, this *dataset* will be consumed by the AI algorithms. On a *Multimodality* visualization of medical images, the clinicians just need to delineate the contours of each lesion, in the presence of a mass. Or just need to mark, by pointing, where are the calcifications on the image. In the end, by consuming this data, the AI algorithms can take into advantage the future integration of automatic agents. Thereafter, the automatic agents will serve clinicians as a second opinion.

2.2 Cancer Detection and Diagnosis

Frequently used in cancer detection and diagnosis, ML has been recently applied for cancer prognosis and prediction. This latter approach is particularly interesting as it is part of a growing trend towards personalized and predictive medicine. In assembling this review, we conducted a broad research of different types of inventions being used, types of data being integrated and the characteristics of these inventions in cancer predictions and prognosis. A number of inventions also appear to lack on appropriate level of features to support our proposed tool for a standardized generation of a *dataset* with medical imaging annotations, in breast cancer, adopting a *Multimodality*[1] strategy. In this section, we will describe several inventions regarding the cancer detection topic, comparing it with our invention proposal.

The first invention, titled as "*Use of computer-aided detection system outputs in clinical practice*" [60], with the US7308126B2 patent number. The invention show the use of Computer-Aided Detection (CADe) system output displays for providing accurate representations of areas for subsequent exams. Since the CADe output is not used during the initial reading, the radiologist does not mark it until a final determination is reached. Furthermore, the indicated regions are shown in the context of a particular anatomical detail. This solution assists the technologist, other physicians and patients in more efficiently and accurately way, locating the exact area for subsequent exams. The work presents several advantages and disadvantages in comparison to our invention proposal. First of all, the work is related and ready for both medical imaging technologies and is applied for the breast cancer domain. Moreover, this work is ready for a *Multimodality* strategy with lesion annotations on a remote fashion. Despite the completeness of this solution, it does not provide a standardized generation of a *dataset* with medical imaging annotations in comparison to our method. Making our solution viable for an invention proposal.

Another similar, yet incomplete solution, is the one titled as "*Method and apparatus for detecting spiculated masses in mammography*" [4]. This work, with the US8164039B2 patent number, presents a method and apparatus to detect one or more spiculated masses in an image using a processor. One big advantage of this work is that the work contemplates a solution for medical imaging technologies, as well as for the domain of breast cancer. Furthermore, this work cover the features for lesion annotations on the MG modality in a remote environment. Despite of these advantages, the work does not cover a *Multimodality* strategy, as it focus just in the MG modality, and does not cover the standardized generation of a *dataset* with medical imaging annotations.

Titled as "*Method for mass candidate detection and segmentation in digital mammograms*" [22], with the US8503742B2 patent number, this invention presents a basic component of CADe systems for digital MG comprising the generation of mass location candidates suitable for further analysis. A component is described that relies on filtering either the background image or the complementary foreground MG detail by a purely signal processing method, on the one hand, or a processing method based on a physical model, on the other hand. The present invention takes into advantage the fact that is prepared for lesion annotations on both medical imaging technologies and for the breast cancer domain. However, it rely on the fact that is limited for the MG modality and it is not prepared for a remote accessibility, as well as does not contemplate the generation of a *dataset*.

Finally, titled as "*Abnormality detection in medical images*" [7], with the US7738683B2 patent number, presents a system for the detection of abnormalities in a medical image of a subject. The system includes an examination bundle, a learning engine, and a detecting engine. The examination bundle includes at least one medical image of the subject from a first modality and at least one medical image of the subject from a second modality. The learning engine is employed for determining the characteristics of abnormalities within at least one medical image from the first modality and at least one medical image from the second modality. The detecting engine is employed for detecting abnormalities within at least one of the medical images comprising the examination bundle. On one hand, this invention takes the advantage of being ready for medical imaging technologies on a *Multimodality* strategy of the breast cancer diagnosis. On the other hand, the disadvantages are the fact that it does not contemplate the lesion annotation on a remote fashion, nor it generates a *dataset* for being consumed by the ML algorithms.

To summarize, several inventions were analyzed regarding the cancer detection and diagnosis topic. By researching those documents and systems, we discover several systems appearing to lack and not fully covering our method and system needs. Moreover, we did not find disclosure for the appropriate level of characteristics and features to support our proposed tool. Even analysing several invention documents, we did not found any solution that directly compete with our invention proposal in terms of cancer detection and diagnosis. However, this section research materials are of chief importance to substantiate our invention proposal.

2.3 Remote and Diagnostic Systems

Nowadays, technology may miss significant and relevant cross information between clinicians [39]. Even though, when leading clinicians diagnose to their patients through several data recordings. Concerning the raised problem, we observe a lack of system features for a remote collaboration between clinicians that should be addressed. In this section, we address the remote and diagnostic systems topic describing the several inventions and demonstrating what are the advantages and disadvantages in comparison to our invention proposal.

Titled as "*Diagnosis Support System Providing Guidance to a User by Automated Retrieval of Similar Cancer Images with User Feedback*" [55], with the US20120283574A1 patent number, the present invention is a diagnosis support system providing automated guidance to a user by automated retrieval of similar disease images and user feedback. High resolution standardized labeled and unlabeled, annotated and non-annotated images of diseased tissue in a database are clustered, preferably with expert feedback. This invention offers the feature of lesion annotations on a remote environment using medical imaging technologies, however, is limited in other ways. Most importantly, it does not provide a standardized generation of a *dataset* with annotations. Moreover, the invention is not ready for a *Multimodality* strategy nor even for the breast cancer domain.

A remote diagnostic system titled as "*Remote diagnostics for a medical imaging system*" [29], with the EP1235510A2 patent number, is described comprising a laptop computer for a service person which can diagnose, test, modify or upgrade a medical imaging system either on-site or from a remote location. Diagnostic information obtained by the laptop computer is thereafter uploaded to the manufacturer where the information is used to understand and repair error conditions and to design future products. This invention relates to medical diagnostic imaging systems and, in particular, to medical diagnostic imaging systems which can be remotely queried, diagnosed, and upgraded. Taking into advantage the fact that it works with medical imaging technologies and on a remote fashion. However, the invention does not comply lesion annotations nor even the *dataset* generation of those annotations. Moreover, the invention does not address a *Multimodality* strategy for the breast cancer diagnosis.

In a method titled as "*Method for operating a medical imaging diagnostic apparatus*" [59], with the US7610075B2 patent number, the inventors describe a method for the operation of a medical diagnosis apparatus in an examination. The method has two main advantages: (1) it is related and proper for medical imaging technologies; and (2) the method generates a *dataset* of the Region Of Interest (ROI) registered with a set of operating parameters of the diagnosis apparatus. In a follow-up examination wherein the ROI is again placed in the imaging volume, a follow-up *dataset* of the ROI is registered with the apparatus operated with the stored, first set of operating parameters and the follow-up *dataset* is stored. Despite of these advantages, the method does not focus on the breast cancer diagnosis and is not ready for a *Multimodality* strategy. Another disadvantage is the fact that this method does not work for lesion annotations on a remote environment.

With the "*Medical imaging and efficient sharing of medical imaging information*" [24] title, and the US20170076043A1 patent number, this invention proposes an image processing and analysis system to identify instances of structure. As advantages, this invention proposes a remote system for lesion annotations on medical imaging technologies. However, the system is not ready for the breast cancer diagnosis on a *Multimodality* strategy. Also, the system does not contemplate the standardized generation of a *dataset* with medical imaging annotations.

Last but not least, titled as "*Medical imaging diagnosis apparatus*" [69], with the US8068651B2 patent number, it includes several ROI settings and configurable units. Despite presenting and relating to the medical imaging diagnosis apparatus, this invention lacks on the other needed characteristics regarding our proposal method and system. Furthermore, the invention only proposes the detection of an optimal scan. Which is not our main goal.

To conclude the present section, we took into consideration a set of inventions regarding the topic of remote and diagnostic systems. It was here where we describe the several inventions, demonstrating what are the advantages and disadvantages in comparison to our proposal.

2.4 Synopsis

In this synopsis, we show an overview of both last two topics: (i) cancer detection and diagnosis; and (ii) remote and diagnostic systems. Table 1 will summarize the characteristics of each invention. The last row of Table 1 shows our proposal method, so that we can compare with the above inventions.

Solution	Med. Img.	Multi.	Breast Cancer	Lesion Anno.	Remote	Anno. Dataset
US7738683B2	X	X	X			
US20120283574A1	X			X	X	
US8068651B2	X					
EP1235510A2	X				X	
US7610075B2	X					X
US20170076043A1	X			X	X	
US8164039B2	X		X	X	X	
US8503742B2	X		X	X		
US7308126B2	X	X	X	X	X	
Our Method	X	X	X	X	X	X

Table 1: List of inventions to compare with our proposal method and system. The first column represent several inventions comparing them to *Our Method*. The following columns are characteristics and features, *i.e.*, *Medical Imaging* (*Med. Img.*), *Multimodality* (*Multi.*), *Breast Cancer Domain* (*Breast Cancer*), *Lesion Annotations* (*Lesion Anno.*), *Remote Environments and Systems* (*Remote*) and *Annotations Dataset* (*Anno. Dataset*), that we wish to cover.

3 Disclosure

Note that the present invention can be implemented as a computer program embodied on a computer-readable medium where the various steps or functions are executed by one or more code segments. A computer-readable medium can be hardware (*e.g.*, one or more processors, integrated circuits, memory, personal data, scientific instruments, etc), firmware or storage media (*e.g.*, one or more hard disks, floppy disks, optical drives, flash memory, compact discs, digital video discs, etc).

All of the disclosed methods and claims herein can be made and executed without undue experimentation in light of the present disclosure. While the methods of this invention have been described in terms of preferred embodiment, it will be apparent to those of skill in the art that variations may be applied to the methods and in the steps or in the sequence of steps of the method described herein without departing from the concept, spirit and scope of the invention. All such similar substitutes and modifications apparent to those skilled in the art are deemed to be within the spirit, scope and concept of the invention as defined by the appended claims.

4 Invention Summary

Our invention works with standard formats supported by medical imaging [53], including the MG, US and MRI modalities. These modalities are available in a standard Digital Imaging and Communications in Medicine (DICOM) format and supported in single-modality by existing systems [31]. Moreover, most systems are general purpose and do not adapt to specific clinical domains (*e.g.*, breast screening). Therefore, they do not provide adequate support to the different clinical workflows [8]. In this invention, we propose a novel tool to be integrated on the clinical workflow. With such tool, the clinical workflow will be ready for automatic agents by the integration of AI algorithms.

The present invention proposes a new framework for a standardized generation of a *dataset* with medical imaging annotations of masses and calcifications concerning breast cancer lesions. The new framework is represented by a novel method and system, working as a medical imaging visualization used in a realistic clinical scenario [62]. The medical images, and respective annotations, are presented in a *Multimodality* strategy. More precisely, the present invention also includes two novel annotating techniques for the medical images: (1) a freehand polygon tool for annotating the masses of breast cancer lesions; and (2) a bullet probe on the image for annotating the calcifications of breast cancer lesions. With a generated *dataset* made by using this new techniques, the clinical workflow can now integrate AI algorithms computing lesion segmentation and classification by automatic agents. Reducing healthcare costs and enabling medical-error mitigation, while in the end it will improve the patient's healthcare [43]. In short, AI has the potential for improving healthcare, complementing expert clinical knowledge to increase diagnostic speed and efficiency.

5 Solution Details

In conjunction with the following figures and diagrams, it will be better understood the specific embodiment of the present solution. In this section, we describe a more complete understanding of the available features and advantages for the proposed invention. While making and using various embodiment items of the present invention are discussed in detail below, it should be appreciated that the present invention provides many applicable inventive concepts that can be embodied in a wide variety of specific contexts. The specific embodiment items are discussed herein and are merely illustrative of specific ways to make and use the invention and do not delimit the scope of the invention. To facilitate the understanding of this invention, a number of terms are defined below. Terms defined herein have meanings as commonly understood by a person of ordinary skill in the areas relevant to the present invention. The terminology herein is used to describe specific embodiment items of the invention, but their usage does not delimit the invention, except as outlined in the claims.

5.1 User Interface

For this invention, the User Interface (UI) consists of two main components: *4. List of Patient Views*; and *5. Medical Imaging Diagnosis Views.* These two main components (Figure 3 and Figure 4) are also divided into several sections: *4.1. List of Patients*; *4.2. Header*; *4.3. Help*; *4.4. About*; *4.5. Study List Tabs*; *5.1. Viewports*; *5.2. Toolbars*; and *5.3. Modality Selection.*

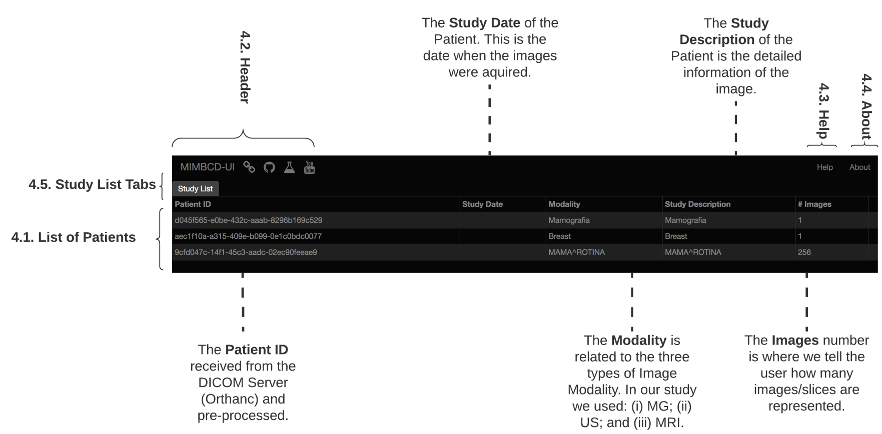

Figure 3: First Screen and List of Patients. The UI components are as follows: *4. List of Patient Views*; *4.1. List of Patients*; *4.2. Header*; *4.3. Help*; *4.4. About*; and *4.5. Study List Tabs.*

5.1.1 List of Patients

The first information (Figure 3) point for the clinician is the *4. List of Patient Views* so that the clinician can quickly choose the respective *4.1. List of Patients* for the task for classifying the breast severity of each patient. This *4.1. List of Patients* contains the most important and needed information avoiding the excess of information typically presented on these systems. On an early work, we potentially improve [8, 9] the temporal awareness of the radiology room[2] with the introduction of these features. The *4.2. Header* represents a shortcut to the *4.1. List of Patients*. Also, if the clinician has some support regarding domain questions, we provide both *4.3. Help* and *4.4. About* components of the UI, by giving clinicians' information how to use our UI. For instance, these components were used by Interns[3], where they took advantage of this information gaining time over diagnostic. The *4.5. Study List Tabs* gives the clinicians' opportunity to switch between the patient who is being diagnosed.

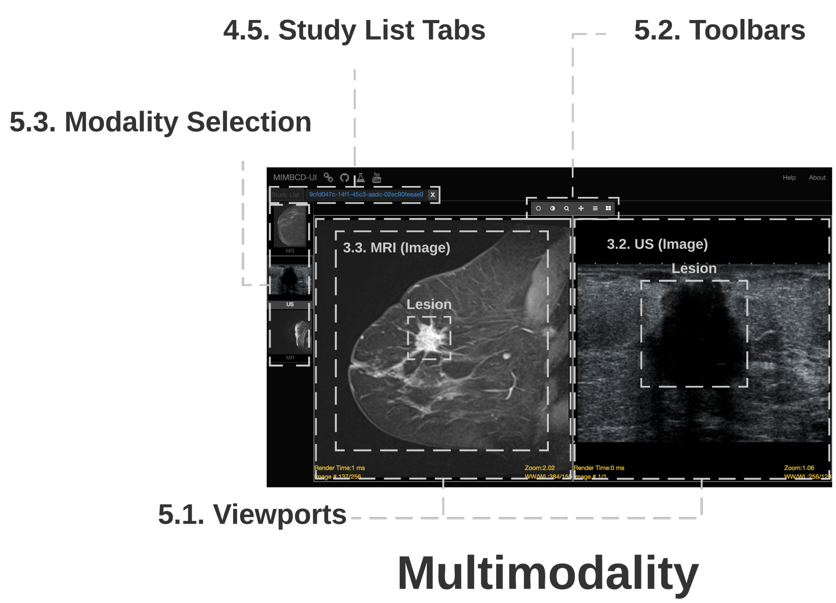

Figure 4: *Multimodality* view. The UI components are as follows: *4. List of Patient Views*; and *4.5. Study List Tabs*; as well as *5. Medical Imaging Diagnosis Views*; *5.1. Viewports*; *5.2. Toolbars*; and *5.3. Modality Selection*.

[2]The **Radiology Room (RR)** is the space in which we have non-invasive imaging scans to diagnose a patient. The tests and equipment involves low dose of radiation to create a highly detailed image of the breast area.

[3]The clinician experience was divided across the following categories: (1) Seniors - between 31 and 40 years of practical experience; (2) Middles - between 11 and 30 years of experience; (3) Juniors - between 6 and 10 years of experience; and (4) Interns - limited experience.

5.1.2 Medical Imaging Diagnosis

Concerning (Figure 4) the point *5. Medical Imaging Diagnosis Views* (*i.e.*, *Viewports*, *Toolbars* and *Modality Selection*) this contributes for the temporal awareness[4] of each clinician. More specifically, the clinician can probe for lesion patterns via the *5.1. Viewports* and processing the image by using the *5.2. Toolbars* (Figure 5) features. Each time the *5.2. Toolbars* functionalities are activated, the clinician needs to perform a simple and easy interaction with the medical image to configure it as desired. Using the *5.2. Toolbars* (Figure 5) on the *5.1. Viewports*, the clinician can locate the lesions and classify the lesions severity (BIRADS). Furthermore, *5.2. Toolbars* (Figure 4) were positioned so as to correspond the clinician's expectations (an outcome of the observations and interviews phases).

5.1.3 Toolbars

Current functions (Figure 5) for image processing includes: *5.2.1. WW/WC* (Window Width/Window Contrast); *5.2.2. Invert*; *5.2.3. Zoom*; *5.2.4. Pan*; *5.2.5. Stack-Scroll*; *5.2.6. Windows*; *5.2.7. Freehand*; *5.2.8. Probe*; and *5.2.9. Save*. These features are included on the *Multimodality* views (Figure 4) of our system.

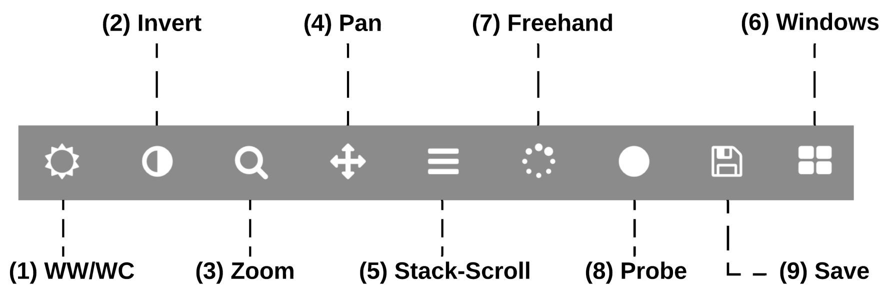

Figure 5: The *5.2. Toolbars* of our system. Currently, the available features are: *5.2.1. WW/WC*; *5.2.2. Invert*; *5.2.3. Zoom*; *5.2.4. Pan*; *5.2.5. Stack-Scroll*; *5.2.6. Windows*; *5.2.7. Freehand*; *5.2.8. Probe*; and *5.2.9. Save*.

The contrast and brightness of images can be adjusted by selecting the 5.2.1. WW/WC (*i.e.*, brightness and contrast) option on the *5.2. Toolbars* and then left-clicking over the image configuring it by moving the mouse at the same time. The same interaction technique is applied for *5.2.3. Zoom*, *5.2.4. Pan* and *5.2.5. Stack-Scroll*. To invert the pixels of the image the user just needs to select the (2) *5.2.2. Invert* on the *5.2. Toolbars*. The *5.2.6. Windows* will open a drop-down list of possible viewport designs (*i.e.*, 1×1, 2×1, 1×2 and 2×2).

[4]We published our statistical analysis regarding those values. For that, you need to have access to the internet. The statistical data page was available on the 6th of February, 2020. (see mimbcd-ui.github.io/statistical-analysis/mm_measures_time_vs_clicks.html)

In this document, we will focus on the delineation of the lesion contours (Section 5.2.1) and respective generation of the annotations (Section 5.2.2). Notwithstanding, the lesion contours are concerning the masses and calcifications regarding the breast cancer disease. On the same hand, the annotations generation is concerning the creation of a standardized *dataset* and storing this information on a remote server. That said, despite highly useful for the patient diagnostic and for the image segmentation (Section 5.2), our focus does not rely on the latter (*e.g.*, *5.2.1. WW/WC*, *5.2.2. Invert*, *5.2.3. Zoom*, *5.2.4. Pan*, *5.2.5. Stack-Scroll* or *5.2.6. Windows*) features. Instead, we are focusing this document on two main features: *5.2.7. Freehand*; and *5.2.8. Probe*. With a third feature being fundamental to *5.2.9. Save* these two features (*i.e.*, *5.2.7. Freehand* and *5.2.8. Probe*) on a remote server.

5.2 Image Segmentation

The system *5.2. Toolbars* are supporting our image segmentation (Figure 6), with the respective features (Figure 4) ordered by user preference. The *5.1. Viewports* are displayed right after the *5.2. Toolbars*, designing around and for medical images what improves the temporal awareness of the task and, in the same time, this invention is supporting the way how to interact with several modalities on a *Multimodality* strategy.

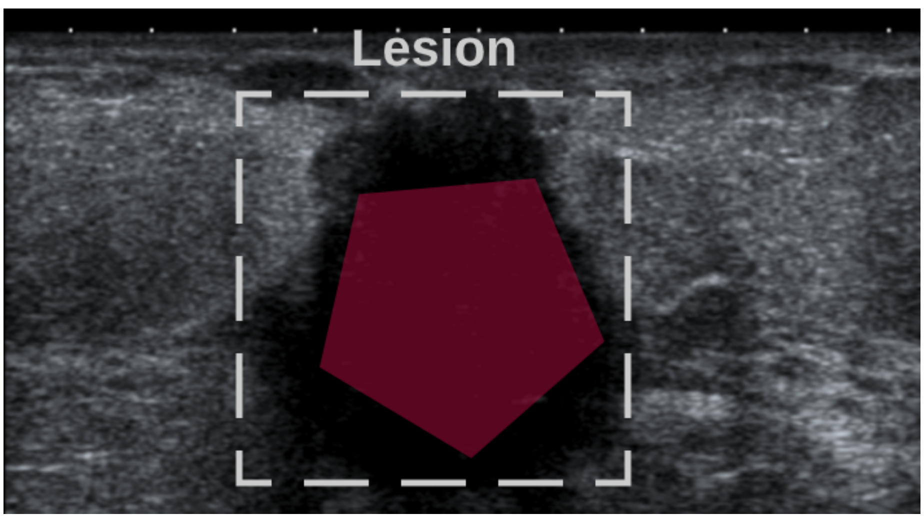

Figure 6: In our definition, medical image segmentation is the process of manually draw for boundaries within our various modalities of images. The goal of the clinician is to annotate the lesion between the red polygon and the dashed gray square.

5.2.1 Lesion Delineation

Manual annotations (Figure 7) are very useful to extract features like contours, intersections, shapes (Figure 1) and image patterns (Figure 2). For a proper classification made by automatic agents, it can be used in the process of lesion delineation and segmentation. In this section, we explain how our method and process works for the delineation and annotation (Section 5.2.2) of medical images. We refer to lesion delineation as the ROI area of the lesion which is delineated by a clinician, such as a radiologist. Further explained (Figure 7), we visually show the relation between the lesion and the delineation.

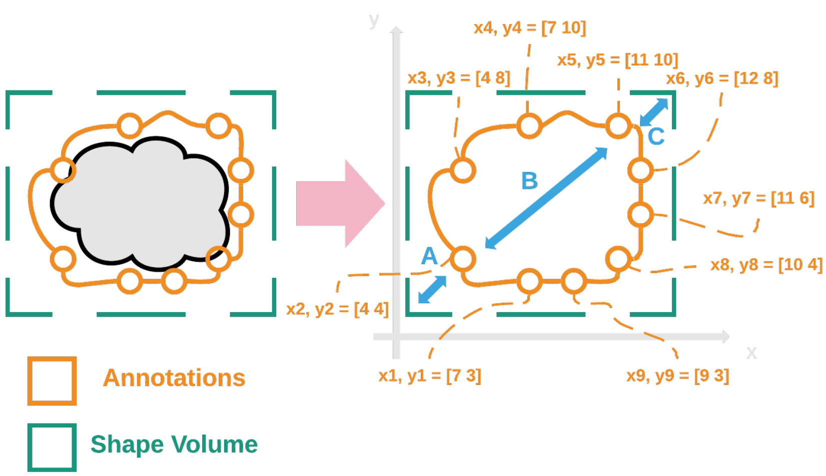

Figure 7: Labels of the Lesions [51] - the grey area is the lesion, the yellow represents the annotations taken by the radiologist, the green represents the shape volume. The image on the right is to explain how the coordinates are represented. The image on the left is how it would appear on the screen.

5.2.2 Lesion Annotations

In this system, the user interact with the UI making bullet points (Figure 7), which can be connected (*i.e.*, *5.2.7. Freehand* feature for masses) or not (*i.e.*, *5.2.8. Probe* feature for calcifications), on the contours of the lesion. Each bullet point is referenced to a `x` and `y` pair of coordinates. The `x` and `y` coordinates (Section 6.1.7) are the position on the image. With this, we can measure the *ground-truth* of the lesion, *i.e.*, **Shape Volume** (Figure 7), and give this information to the ML algorithms. Also, it is now possible to autonomously classify the margins and shapes of masses (Figure 1) and the distribution patterns of calcifications (Figure 2).

6 System Description

The goal of this section is to describe the properties and environment characteristics of the system, having a base architecture already implemented [9]. As explained before, the purpose of this invention is to work on the **RR**. This means that it must be adjusted to a traditional environment (*e.g.*, computer desktop, keyboard and mouse in a dark room), and reliable due to the personal and medical stored information. Given this situation, we need a secure but easily accessed system for clinicians to work with. Our invention is a distributed system that allows a secure and easy access to information and the manipulation of medical images. With this kind of image manipulation, in our case the annotation of the images, the community can train the ML algorithms.

6.1 Technologies

Concerning the selected technologies, our decision relies on the available and powerful technologies from the Open Source (OS) community. Our selection criteria was based on robust technologies which will mitigate the limitations of this invention. For this reason, all the decisions must be balanced. Thankfully, many selected technologies are heavily used by the OS community, making it strong and robust for the purpose. Nevertheless, it must be underlined the following. Although we are using OS technologies for this invention, they will serve as a *proof-of-concept* only and are serving in our research work. The purpose of this invention is to propose the method and the process by the use of a system. And not specifically, *as-is*, the system technologies. The technologies can be changed according to the needs of both domain and environment. Therefore, a conflict between OS technologies and this invention does not exist.

6.1.1 Source Code

To maintain the system, our source must remain simple and secure. Moreover, the source must provide functionalities such as storing medical exams, use browsers to run the solution and must be a remote distributed system. By choosing where to present the system, namely in a browser, we choose to use JavaScript as the programming language to run and manipulate the medical images. With this programming language it is possible to manipulate those DICOM [70] files. Thereafter, we used a library focused on medical imaging manipulation, CornerstoneJS[5], which we will explain in detail later. We will also need to have image visualization for what we use Vanilla JS[6], which we will also explain in detail later. In terms of source code, the web application uses JavaScript, which is an Object Oriented (OO) language, HyperText Markup Language (HTML) and Cascading Style Sheets (CSS) technologies. This source is powerful and flexible. Based on this, we are going to use all three of them in this invention as a *proof-of-concept*.

[5]Link: cornerstonejs.org
[6]Link: vanilla-js.com

The JavaScript allows multi-paradigm approaches, such as:

1. **Client-Side** Scripting Language - runs on the computer browser;
2. **OO** Language - each "object" has its attributes and methods;
3. **Interpreted Language** - doesn't need to be compiled;
4. **Imperative** and **Declarative** - can change the state and show what it's doing but not how it is doing, respectively;
5. **Functional** Language - has mathematical based functions.

We are basing our JavaScript technologies on the **JQuery** library for the HTML manipulation, event handling, and `dicomParser`[7] (parse the DICOM files), because it simplifies the coding. However, these technologies do not add functionality, but instead, are simplifying the code and minimizing it. What is great for system maintainability purposes. The above mentioned languages are used to develop all invention features. Such technologies, are giving us the ability to make the visual representations on an easily way.

Our invention was implemented using CornerstoneJS [72] with a *NodeJS* server. To populate the system, the user can upload sets of patients' images into an Orthanc Server [36]. Each patient has three modalities (MG, US and MRI). The images can be pre-processed and anonymized on the Orthanc Server and then consumed by the system. This system is designed as a set of modules that can be reused in other applications. The CornerstoneJS family of libraries are providing essential functions, such as (i) image rendering; (ii) DICOM retrieval; (iii) tool support; and (iv) interpretation (UI).

6.1.2 DICOM Format

The DICOM format[8] is normally used to store medical images [70] and is a standard in medicine. Supporting a wide variety of medical information (*e.g.*, exam images, structured reports, etc), it also has the benefit to convert known file formats such as JPEG and MPEG. The medical information encoded by a DICOM file (Figure 8) is called a *dataset* and takes the form of an associative array. Each value can itself be a list of *datasets* (Section 6.1.7, leading to a hierarchical data structure that is much like a JavaScript Object Notation (JSON) file. In the DICOM terminology, each key is called a DICOM tag. The list of the standard DICOM tags is normalized by an official dictionary. For improved readability, it is also common to name these DICOM tags (e.g., "PatientName" or "StudyDescription"). The standard associates each DICOM tag with a data type, that is known as its value representation. We are going to use this technology to store the exam and patient information.

[7]Link: github.com/cornerstonejs/dicomParser
[8]Link: link.medium.com/LNZ5glN1c4

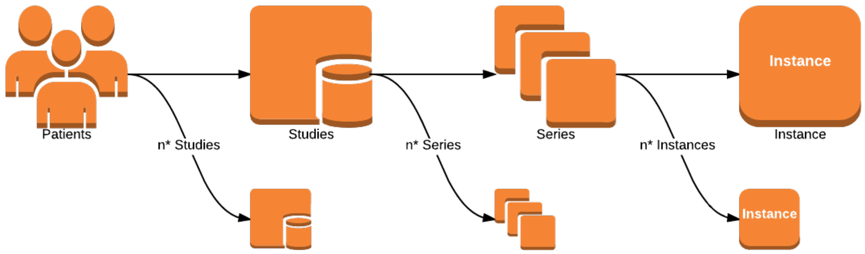

Figure 8: This diagram [12] shows that a given patient benefits from a set of medical imaging studies. Each study is made from a set of series. Each series is, in turn, a set of instances.

6.1.3 PACS

The PACS [21] offers efficient storage and a simple way to access the (DICOM) images in a variety of modalities. The deployment of these technologies requires specific packages and environments, which will be detailed below. Our platform provides essential tools for the deployment of *Multimodality* strategies, interactive image visualization/manipulation, and study navigation in a web browser. This paves the road for the integration for *Multimodality* strategies into PACS as it only needs a web browser which is always accessible on the clinical workstations.

6.1.4 DICOM Server

We are going to use the Orthanc Server [36] distribution to store the medical images. The advantage of using an Orthanc Server is that it is a lightweight server for medical imaging (PACS) and it is an OS project with a free software license. It, also, has the capability of managing and analyzing all of the contents (Figure 9), and it offers the possibility of visualizing the images in the web browser. A DICOM server, like the Orthanc Server, its built-in RESTful API[9] [35]. It can be used to drive it from external applications. For instance, the CornerstoneJS set of tools and originated platforms. The Orthanc uses several DICOM tags from the stored medical images in the JSON file format. The structures for the stored DICOM resources are fourfold identifiers: (1) Patient; (2) Study; (3) Series; and (4) Instance.

[9]This REpresentational State Transfer (RESTful API) is a well-documented set of HTTP paths against which it is possible to make HTTP requests with any client tool, such as the standard curl command-line tool. Similarly to Orthanc Explorer, the RESTful API is served through the embedded Mongoose HTTP server.

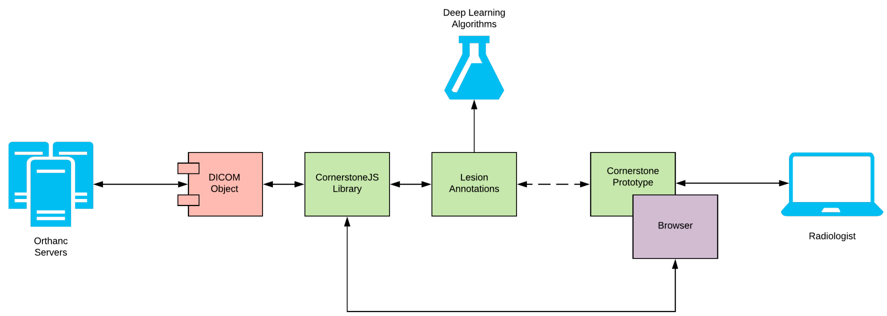

Figure 9: Image retrieval from the Orthanc Servers [11] to the DICOM viewer. In this figure, the DICOM viewer is supported by both CornerstoneJS library and Cornerstone Prototype. Now, radiologists can annotate each lesion providing this data to the DL Algorithms.

6.1.5 Main Server

Similar to other systems [32], our invention utilizes a Front-end and a Back-end ecosystem integration for content management, image storage, and image display. In this section, we describe how our web-based system (Figure 10) was created with a Back-end architecture. By utilizing a common JavaScript framework called NodeJS, we integrate it into an existing ecosystem (*i.e.*, with CornerstoneJS and Orthanc Server). The Back-end comprises the web server and the image storage, as well as content management, and was created with OS technologies and data storage protocols. Metadata was stored and retrieved using a SQL and JSON database. The web server was written in JavaScript using NodeJS, an OS server-side Back-end implementation of the JavaScript programming language that is powered by V8 JavaScript engine. NodeJS is a platform built on JavaScript runtime for easy building of fast, scalable network applications on all the operating systems. Furthermore, NodeJS uses an event-driven, non-blocking Input/Output (I/O) model that makes it lightweight and efficient, suitable for data-intensive real-time applications that run across distributed devices. As a WebSocket library, NodeJS was used for the WebSocket communication. The net module, which provides asynchronous network wrapper for creating both Transmission Control Protocol (TCP) servers and clients, was used. The NodeJS server listens on two ports for incoming DICOM or WebSocket connections. By using a PACS (Section 6.1.3) and a DICOM Server (Section 6.1.4), the NodeJS server knows what image size to expect from incoming TCP connection. When this data is received, the DICOM server sends the image to the web client over WebSocket connection. We need to follow this method since, in web browsers, JavaScript does not support access to TCP/IP protocol or DICOM protocol. Making it vital to apply this method.

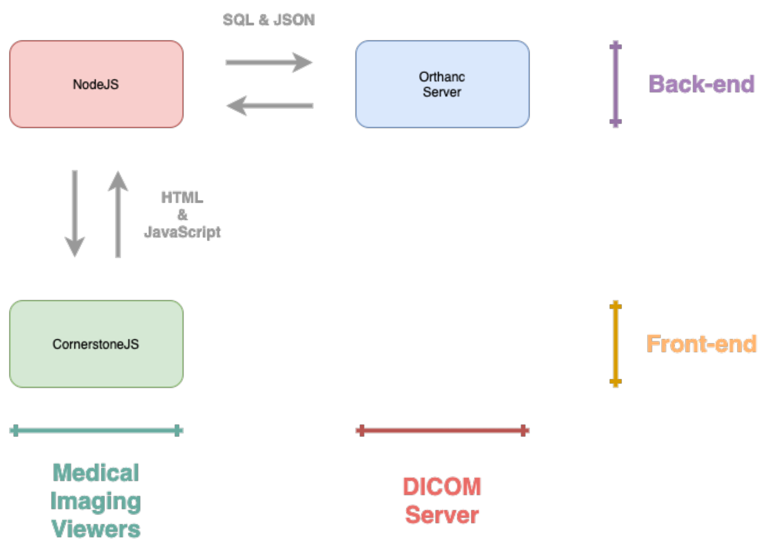

Figure 10: [DOI: 10.13140/RG.2.2.13834.62405] Schematic demonstrating both **Front-end** and **Back-end** components of the system with integrated medical imaging solutions. In our solution, we show the use of technologies such as **NodeJS** and **CornerstoneJS** for the **Medical Imaging Viewers**, as well as the **Orthanc Server** for the **DICOM Server** component [14].

6.1.6 Medical Imaging Viewers

The CornerstoneJS [66] is an application that performs the rendering, the download and some other functionalities with the images. We are going to use it for all of those features. Moreover, we are going to use this tool to operate the images (Figure 10), making use of functionalities such as zoom, contrast, etc. Cornerstone is an HTML5 and JavaScript-based library. The library can display interactive medical images on any modern browser that supports the HTML5 canvas element. This includes desktops, mobile devices, and tablets. In short, the library is a zero-footprint viewer enabling access to images on a browser without requiring installation of additional software. Similar types of online medical imaging systems have been previously reported in the radiology literature [32]. Those systems are supporting a full range of standard image viewing and manipulation functions including *Multimodality* viewing with zoom, pan, and window and level. Annotation of masses and calcifications (Section 6.1.7) is also implemented, allowing measurements of the lesion types, such as margins and shapes of masses (Figure 1), as well as calcification types (Figure 2). Measurements for the Regions Of Interest (ROI) where developed, with the ability to draw among lesion masses and to bullet point the calcifications.

6.1.7 Annotated Data

Our solution, will enable ML communities to organize and promote medical imaging projects. As result of our generated *dataset* (Figure 11), the community can now have access to a tool, creating their own *datasets* of medical images and annotations, respectively. With our solution, the community has now a way for the data extraction of lesion annotations among the breast cancer disease. This data is saved to a set of JSON files, one per each patient, where each file has JSON objects organized into a standard structure. Now, the extraction of the latter data, *i.e.*, JSON objects, requires specialized knowledge and understanding of the data structure. As follows, we will explain our annotations data structure for the JSON files generation from user interactions.

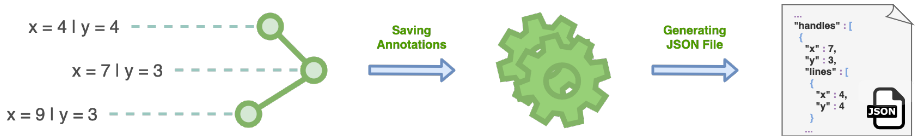

Figure 11: [DOI: 10.13140/RG.2.2.33967.28323] Schematic diagram for the annotations flow and JSON file generation [13].

Further operations applied to patient studies on a *Multimodality* strategy are propagated though an indirect mechanism [1]. Instead of congesting the network with image data of annotated masks, JSON objects[10] typically fitting in IP packets are transmitted. Reducing the communication time and, consequently, improving scalability of the solution. In our system workflow (Section 6.1.8), it leads to a JSON objects broadcast with average size of 20 KB per annotation. Meaning that, each time an image as a lesion (*i.e.*, mass or calcification), clinicians will generate a file with the size of $20 \times L \times I$. Where L is the number of lesions on an image, and I is the number of images from a patient.

By selecting (Section 5.1.3) the *5.2.7. Freehand* (*i.e.*, the `freehand` tag of the JSON file) or the *5.2.8. Probe* (*i.e.*, the `probe` tag of the JSON file) feature (Figure 5), we will generate an array of objects. Each object is a list of variables, which are referencing the sate, *i.e.*, `visible` and `active`, of the annotations. The last variable, *i.e.*, `handles`, is the array of objects with the coordinates, *i.e.*, `x` and `y`, of the annotations. Moreover, each `handles` object has another three state variables: (1) `highlight`; (2) `active`; and (3) `lastFlag`. Last but not least, each `handles` object has also an object of `lines`. The `lines` are sets of objects where each object (*i.e.*, child coordinates) represents all `x` and `y` coordinates of a parent. However, in this solution each `x` and `y` parent coordinate have one, and only one, associated `x` and `y` child coordinate. Because of that, we called this variable as `lines`, since the variable refers to the visually connected line between child/parent coordinates.

[10]**JSON objects** are surrounded by curly braces and are written in key/value pairs. Keys must be strings, and values must be a valid JSON data type (string, number, etc). Keys and values are separated by a colon. (see w3schools.com/js/js_json_objects.asp)

The following snippet, shows a possible sample of a JSON source by following the Figure 7 example:

```
"freehand":[
  {
    "visible":true,
    "active":false,
    "handles":[
      {
        "x":7,
        "y":3,
        "highlight":true,
        "active":true,
        "lastFlag":false,
        "lines":[
          {
            "x":4,
            "y":4
          }
        ]
      },
      ...
      {
        "x":9,
        "y":3,
        "highlight":true,
        "active":true,
        "lastFlag":false,
        "lines":[
          {
            "x":7,
            "y":3
          }
        ]
      }
    ],
    "highlight":false
  }
]
```

The value of `freehand`, `probe`, `handles` and `lines` must be one array of objects. The values of `visible`, `active`, `highlight` and `lastFlag` must be boolean (*e.g.*, `true` or `false`). Finally, the values of `x` and `y` coordinates must be *integers* or *floats*.

6.1.8 System Architecture

Hereinafter, we will explain briefly how a diagnose and lesion annotations are performed (Figure 12) by a clinician using our system invention. A more detail explanation will be given at the end of this section. First of all, clinicians acquire the patient images and perform a medical exam that is then stored as a DICOM file (Section 6.1.2) on the DICOM server (Section 6.1.4). Thereafter, the clinician will open the browser and an Orthanc connection, signing in with the medical credentials (Section 6.1.3). After the connection is completed, the browser will request (Section 6.1.5) the available image to the server and present (Section 6.1.6) them to the clinician through the UI. By opening a patient case the clinician will visualize the DICOM files and manipulate those using the available tools. After analysing the medical exams, clinicians will diagnose the patient.

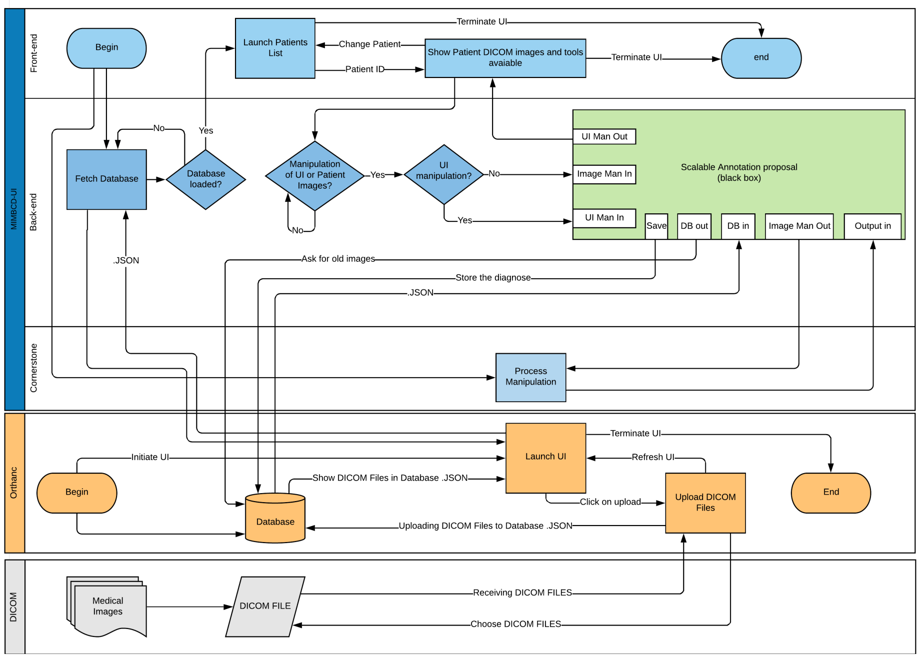

Figure 12: System architecture of the invention with a black box of scalable interactions.

After the **Orthanc Server** is launched and the database is ready, it will stay on standby, waiting for requests. All patient images available to the clinician are requested by the system to the **Orthanc Server** and if the response given is successful, a JSON file is received. After a successful database fetch, it is reported back to the clinician the list of patients available for diagnose. The clinician will now choose a patient to diagnose and a UI of the system, and it will show all the available images on the left (Figure 4) side of the screen.

7 Proposal Overview

Screening helps diagnose breast cancer at an early stage, when treatment is more likely to be successful, ensuring more people survive the disease [46, 65]. However, it also has harms such as diagnosing cancers that would never have gone on to cause any problems and missing some cancers [30]. Which reflects on a higher number of false positive and false negative values [26, 80]. Opening the potential for AI to improve breast cancer screening and ease pressure of the several National Health Systems around the globe, by mitigating those false positive and false negative numbers [23, 47]. As more AI screening tools enter the clinical market, the needs for more and better data is growing. In this section, we explain the overall of our proposal showing information regarding commercial interest of the proposed invention.

7.1 Proposal Motivation

With the hype of AI methods, such as ML and DL algorithms, automatic (*AI-Assisted*) agents are closer to the radiology room than ever [40]. This proximity, makes highly relevant to the ML community, whom is showing interest on solutions for *dataset* generation among medical imaging. The *datasets* are generated by an oracle (*e.g.*, clinicians, radiologists, etc), having more supervised data [6, 84] to train their methods. A greater stakeholder engagement is requiring sufficient validation and continuous monitoring of emerging AI tools, as well as the available data from breast cancer screening. That said, National Health Systems are on the need for methods, such as our invention, to a continuous monitoring and re-calibration of these AI tools.

7.2 Stakeholders

Several of these AI tools have garnered medical regulatory approval within multiple countries, including Portugal and other European Union (EU) members [56, 73]. With the approval of this medical regulatory, these commercial products can now be marketed for clinical use directly to stakeholders such as radiologists and physicians. However, key stakeholders, including major payers, service providers, and women undergoing routine screening, need convincing evidence that these new tools can reliably improve screening performance beyond current practice standards. For instance, by reducing the numbers of false positive and false negative values. But given the “black box” nature of AI algorithms, there are a number of unique challenges in the process of algorithm validation and stakeholder acceptance. There is a myriad of ethical, social, political and technical issues regarding AI algorithm validation. Thus, there is some work to do regarding major pressing issues in validating those methods from the perspective of regulatory agencies, organizations with imaging data, and AI researchers. In our work, we already formulated two collaborative protocols with: (1) Hospital Fernando Fonseca; and (2) IPO Lisboa. The purpose of these protocols is the interchange of data and knowledge.

7.3 Invention Development Stage

A significant number of technologies under development and in prototype or clinical trials (Figure 13) suggest that AI-powered diagnostic departments will feature in many future clinical institutions [5]. Diagnostic institutions are leveraging pattern recognition and DL to reduce diagnosis turnabout time, and improve pathology workflow accuracy and efficiency of the diagnostic.

Technology	TRL	IP Publication	Academic Publications
Deep Learning	9	243,000	162,000
Speech Recognition	8	238	221,000

Figure 13: Analysis of the market [5] on the Technology Readiness Level (TRL), Intellectual Property (IP) Publications and Academic Publications for AI in diagnostic and imaging domain of healthcare. The analysed technology levels are Deep Learning (DL) and Speech Recognition (SR).

Given the speculative importance of our invention to the industry, we have conducted a market overview analysis of how the technology will impact the clinical domain of breast cancer diagnosis. Furthermore, we compare the current technology maturity of the invention with this analysis. To simplify the comparison, we will use Technology Readiness Level (TRL) [25] which have been used to grade the maturity of our invention. The TRL is a measure of the progress stage (Figure 14) that health research is making toward improved clinical practices and processes and their implementation into real-world contexts.

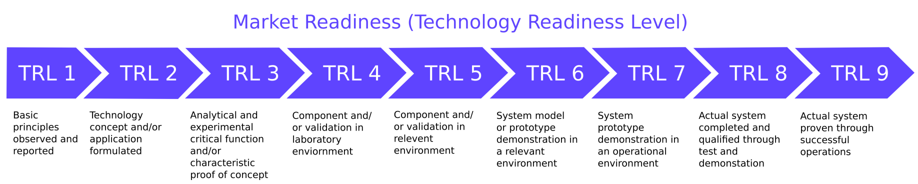

Figure 14: Healthcare sector strategy has been steered by TRLs. The high value have been established to focus on the applied R&D stages between **TRL4** and **TRL6**. And many grants and funding mechanisms define application suitability using TRLs.

Currently, our invention follows a **TRL6**, meaning that the system prototype was already demonstrated in a relevant environment. In fact, we already studied our solution with 45 clinicians recruited on a volunteer basis from a large range of clinical scenarios (distinct health institutions in Portugal). However, the present levels (Figure 13) of both DL and SR are higher. Typically, DL levels are staged at **TRL9**, while SR levels are staged at **TRL8**.

In a near future, we aim to leverage the TRL stage to a higher level. After concluding this invention proposal, our purpose is to increase the invention levels of maturity. The goal is to go from **TRL6** to **TRL8**, at least. We will do that thanks the collaborative support of the various clinical institutions in Portugal and the already accomplished protocols. As follows, we list the number of clinicians involved in our last study, as well as the several institutions.

Number of clinicians and institutions that supported our project:

- 12 clinicians of Hospital Professor Doutor Fernando Fonseca (HFF);
- 10 clinicians of Instituto Português de Oncologia de Lisboa Francisco Gentil (IPO-Lisboa);
- 2 clinicians of Hospital de Santa Maria (HSM);
- 9 clinicians of Instituto Português de Oncologia de Coimbra Francisco Gentil (IPO-Coimbra);
- 1 clinician of Madeira Medical Center (MMC); and
- 1 clinician of Hospital Serviços de Assistência Médico-Social (SAMS);
- 8 clinicians of Centro Hospitalar Barreiro Montijo (HB);
- 1 clinician of Hospital Santo António (HSA);
- 1 clinician of JCC DIAGNOSTIC IMAGING (JCC);

In that study, we conducted an evaluation of this invention simulating real-world conditions with 45 clinicians in nine different clinical institutions, as above mentioned. Our goal was to quantitatively and qualitatively assess the invention maturity that our system embodies, and to understand how these method, as well as process, would work in practice. From the demographic questionnaires: 24.4% of the clinicians have between 31 and 40 years of practical experience (seniors); 31.1% have between 11 and 30 years of experience (middles); 17.8% have between 6 and 10 years of experience (juniors); and 26.7% have limited experience (interns). Interviews were conducted in a semi-structured fashion taking about 30 minutes. Overall, 57 days were spent on the clinical institutions for the observation process and six months for the classification using our invention. In the end, for each participant we applied both SUS[11] [71] and NASA-TLX[12] [58] scales, as well as a *post-task* questionnaire.

[11]For SUS scores, we used a 5 item scale. The scores range from 1 - "**Strong Disagree**" to 5 - "**Strong Agree**". The mean across all individual questionnaires was computed over studies. We provide an available *dataset* from our SUS data. (mimbcd-ui.github.io/dataset-uta7-sus)

[12]For NASA-TLX scores, we used a 20 item scale. The scores range from 1 - "**Very Low**" to 20 - "**Very High**". Again, we provide an available *dataset* from our NASA-TLX data. (mimbcd-ui.github.io/dataset-uta7-nasa-tlx)

To conclude, development of AI tools may allow identification and quantification of early discoveries in complex medical images that current experts are not able to recognise. In several countries [2], AI has been used to review and translate MGs 30 times faster than doctors with 99% accuracy. This benefits such as reduction in the need for unnecessary biopsies and reducing the patient stress of misdiagnosis. In the diagnostic arena, our invention will play a fundamental step on this novel paradigm. Moreover, our tool was already successfully tested with 45 clinicians among nine clinical institutions. We properly tested the acceptance and usefulness of the tool on a real-world scenario using quantitative measurements and qualitative, such as time, number of errors, observations, interviews and clinicians feedback. As already referenced, we also used SUS and NASA-TLX to measure usability and the workload impact, respectively. All results showed to be successfully tested and clinicians showed a highly acceptance for this tool. Despite of the good results, after this invention proposal we aim to increase the maturity of this invention from **TRL6** to **TRL8**. So that we can integrate the invention on the market to solve a huge problem (Section 7.4) on the breast cancer diagnosis.

7.4 Problem Solution

Clinicians, such as radiologists, are key people for several current AI challenges [56]. They do that by creating high quality training *datasets*, but also by doing the interpretation of the obtained results, and definition of the clinical task to address. Radiologists may play a pivotal role in the identification of clinical applications where AI methods make difference. Indeed, they represent the final user of these technologies. Radiologists are the ones who knows where these technologies can be applied to improve patient care. For that reason, radiologists point of view and feedback are crucial to optimize the use of AI-based solutions, such as our invention.

Concerning our invention, we are solving five key problems: (a) providing a tool to improve a method and process for the curation of sufficient image data on AI algorithm development and evolution supporting medical imaging; (b) promoting the generation of medical imaging *datasets* to be compared by several AI methods among the literature; (c) also providing a tool for clinicians to collaborate each other on a remote and distributed system; (d) bringing together several medical imaging modalities on a *Multimodality* visualization strategy; and (e) offering the opportunity for clinicians to diagnose each patient with the above characteristics and in the same time generate a *dataset* while just interacting with the UI.

By solving this five key points, we will address several market opportunities (Section 7.5) with our solution, as well as in further inventions. Actually, AI is driving factor behind market growth in medical imaging. By 2023, AI in medical imaging[13] will become a $2 billion industry. Making it vital to have a solution, as the one proposed in this invention, to solve those five problems.

[13] Link: signifyresearch.net/medical-imaging/ai-medical-imaging-top-2-billion-2023

To conclude, the market (Section 7.5) has mainly been driven by many researchers and developers who are applying ML to medical imaging. However, the major medical imaging services are now ramping-up their AI activities. Therefore, addressing our competitors (Section 7.6), as well, will be an essential function in this document.

7.5 Commercial Applications

In terms of research, a number of academic laboratories are developing AI technologies, for applications to medical imaging. There are commercial possibilities afforded by AI on breast cancer diagnosis. From our invention, we will address a fourfold of medical applications including the fields of: (1) Medical Imaging Analysis; (2) Computer-Aided Diagnosis (CADx); (3) Breast Cancer Screening; and (4) Medical Imaging AI-based Assistants. But first, we need to describe where and how each field is related with our invention in medical applications. We will address each field, while providing (Section 7.6) comparison samples.

With a potential for commercial application, the first field to address is Medical Imaging Analysis. Here, technologies are based on medical images, in which these technologies identify anomalies and diseases with higher accuracy than clinicians. Such tools are made to satisfy the basic tumor metrics workflow of small cancer centers, whatever is the same purpose of our invention. Furthermore, compatibility with common image analysis tools facilitates radiologist engagement in image data curation, including image annotation. *Datasets* of image annotations are supporting AI application development and evolution for medical imaging.

The second field to address is CADx. CADx tools are used in the diagnosis of breast cancer, lung cancer, etc. A CADx identify abnormal signs at an earliest that a human professional fails to find. These tools are made to provide precise, powerful healthcare solutions expertly engineered to optimize operational efficiency, clinician confidence and patient outcomes. With our invention, we can easily extend the current features to a CADx system.

Thirdly, we will address Breast Cancer Screening field of application. In this field, a set of tools for breast cancer estimations are showed. These tools have the purpose of looking for signs on the disease, before a person has symptoms. What is exactly where our invention is inserted. It is clear that the application of ML methods can improve the accuracy of breast cancer prediction outcomes. With our invention, the community will achieve that by having a method that will promote the existence of a curated *dataset* on medical imaging.

Last but not least, the fourth field is Medical Imaging AI-based Assistants. In this field, medical applications are designed to optimize productivity and accelerate workflow with a whole set of diagnostic imaging tools for every kind of modality study on one workstation. From these tools, AI is able to interact seamlessly with users via text, expedite necessary information at relevant points of care, provide clinical decision support with reading aids, and more. Our invention will augment this functionality by offering higher data curation from radiologists.

To conclude this section, it summarize several fields for commercial applications of our invention in the breast cancer diagnosis. Some of these applications, were proposed just to solve problems on small cancer centers. On the other hand, we show existence of tools with technology maturity to provide precise and powerful healthcare solutions. Moreover, it was in this section that we describe tools where the purpose was to automatically discover signs of the disease, before a patient has symptoms. Finally, we describe tools offering AI algorithms which are able to interact with users, providing clinicians with a decision making system. We can apply our invention to all of these fields and market segments. In fact, some of the above mentioned commercial applications are direct competitors (Section 7.6). However, they do not offer a complete solution as ours. Making this invention a true novel solution.

7.6 Competitors

Across the diagnostic arena, several of the most well-known players include IBM Watson Health (ibm.com/watson-health) and Google Health (health.google). Hospitals and clinical centers have been adopting cognitive computing solutions such as IBM Watson to diagnose breast cancer much earlier, with demonstrated benefits of creating higher healthcare results for patients. In this section, we describe and address our several competitors. Our competitors assume various forms of developments. From R&D projects, to products/services, or even companies, we describe how they start and have been developed.

7.6.1 Projects

In terms of projects, both academy and industry are active promoting the development of healthcare solutions. On the academic front, researchers at Carnegie Mellon University are working on several healthcare initiatives, combining medical sensors, robotics and AI to create a new field that will improve patient care on the clinical institutions. Projects like GymCam, In Situ Imaging and "Unremarkable AI" are helping patients and physicians on their daily basis. Another propelling famous institution is Stanford University, where researchers are developing projects with significant improvements to people's lives through healthcare solutions. Two important projects on the medical field are CheXpert and MRNet. The first, *i.e.*, CheXpert project, is a large dataset of chest X-rays and competition for automated chest x-ray interpretation, which features uncertainty labels and radiologist-labeled reference standard evaluation sets. The second, *i.e.*, MRNet project, consists of knee MRI exams, containing several labels in which were obtained through manual extraction from clinical reports. Despite of the great contribution from academy, companies (*i.e.*, industry) are also increasingly partnering with hospitals and research institutions to develop healthcare solutions. Johnson & Johnson has embarked on a joint with several institutions to create new healthcare projects. Similarly, IBM Watson Health and Google Health are partnering with a number of hospitals and research institutes.

7.6.2 Products & Services

Beyond the field of Medical Imaging Analysis and respective commercial applications, we have the following examples: (1.1) ImageJ [64]; (1.2) ITK-SNAP [81]; (1.3) OHIF [85]; (1.4) AMIDE [45]; (1.5) FSL [34]; (1.6) MITK [77]; (1.7) OsiriX [61]; and (1.8) 3D Slider [27]. ImageJ was developed at the National Institutes of Health (NIH) by an employee of the Federal Government in the course of his official duties. ImageJ is an experimental system. On the contrary, ITK-SNAP is a commercial application. AMIDE is a competely free tool for viewing, analyzing, and registering volumetric medical imaging *datasets*. FSL is a comprehensive library of analysis tools for fMRI, MRI and DTI brain imaging data. OsiriX provides a high performance and an intuitive interactive user interface as a DICOM viewer. Open Health Imaging Foundation (OHIF), Medical Imaging Interaction Toolkit (MITK) and 3D Slider are open source software platforms for medical image informatics, image processing, and three-dimensional visualization. From the field of CADx, we have the following examples: (2.1) iCAD; and (2.2) ImageChecker. Both are providing innovative cancer detection and therapy solutions. Also, iCAD and ImageChecker are providing precise, powerful healthcare solutions expertly engineered to optimize operational efficiency, clinician confidence and patient outcomes. Beyond the field of Breast Cancer Screening, we have the following examples: (3.1) Breast Cancer Risk Assessment Tool; and (3.2) Breast Cancer Screening (PDQ)-Patient Version. Both tools are using a patient's personal medical and history to estimate absolute breast cancer chances or probability of developing invasive breast cancer. Finally, for the field of Medical Imaging AI-based Assistants, we have the following examples: (4.1) PaxeraUltima; and (4.2) PaxeraRIS. The PaxeraHealth solutions are designed to optimize productivity and accelerate workflow with a whole set of diagnostic imaging tools for every kind of medical imaging study on one workstation.

7.6.3 Companies

A number of companies for healthcare development, are investing large amounts of funds to promote, not only research projects (Section 7.6.1), but also, their own products & services (Section 7.6.2) to be commercialized. Companies like Alphabet and IBM are developing their own solutions for healthcare such as Google Health and IBM Watson Health, respectively. In terms of medical imaging, players like Pixmeo, Nucleus.io, ASCEND, Radical Imaging and PaxeraHealth, are solving medical imaging informatics, interoperability, and integration challenges for their clients in healthcare. The Pixmeo is the company who developed the OsiriX platform. Nucleus.io is a technology and medical services company contributor of the OHIF platform, as well as the CornerstoneJS library. The company is focused on medical image management and interpretation. ASCEND and Radical Imaging are companies which are improving diagnostic care and patient outcomes through intelligent solutions and seamless integration. Finally, PaxeraHealth is developing solutions for medical imaging AI-based assistants.

8 Conclusions

In this document, we propose a new method and process supported by an interactive UI of a system platform. More precisely, the purpose of this UI is to generate a standardized *dataset* of medical imaging annotations. Across the domain of breast cancer, we adopt a *Multimodality* visualization strategy (*i.e.*, MG, US and MRI) in order to provide clinicians a tool for the production of those qualified *datasets*. In the end, we foster clinicians' sharing and collaborative evaluation by developing a distributed, as well as remote accessible system (Section 1). From the beginning of the document, it is explained how the above system will provide a solution on the clinical domain (Section 2). With our methods and claims disclosed (Section 3), the document guarantee the formal execution of the invention. In the end, the outputs (Section 4) of our invention will reduce healthcare costs, enabling medical-error mitigation, while improving the patient's healthcare. We achieve that due to the various embodiment items of this invention (Section 5), discussing in detail the available features of the system. The properties and environment characteristics (Section 6), also underline the system description of the invention and how it will be addressed to work on the **RR**. Last but foremost, the document is concluded in a proposal overview (Section 7) of commercial interest and applications.

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