

MIDA

User Testing Guide

Multi-Modality vs AI-Assisted

Assistant Introduction

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Prototype: prototype-multi-modality
Milestone: 1.2.0-beta

Version: v1.0.1-alpha
Release: v1.2.0-beta

Prototype: prototype-multi-modality-assistant
Milestone: 1.2.0-alpha

Version: v1.2.0-alpha
Release: v1.2.0-alpha

DICOM: dicom-server
Commit: 80191e9941c24043c7f612b2dadcd415c060bf96

Depl. Env.: Localhost
Link: breastscreening.io/dashboard

Depl. Server: Localhost

Main Server: Localhost
Private IP: localhost
Private Domain: localhost

Port: 8486
Public IP: localhost

DICOM Server: Localhost
Private IP: localhost
Private Domain: localhost

Port: 8448
Public IP: localhost
From: 8448

1 Introduction

This document aims to describe the protocol and guidelines of the presented information. We perform a set of tests in the scope of both v1.0.1-alpha and v1.0.1-alpha versions from both prototype-multi-modality and prototype-multi-modality-assistant repositories. The repositories are part of the MIDA project using traditional devices (mouse and keyboard). The goal of the test is to compare both prototypes, measuring the user performance, efficiency and efficacy metrics. The sessions will be recorded via video on a computer and using a record heat-map, while triggering event tools. It is guaranteed the confidentiality of the recordings, which will be used only for academic purpose. Also, we will use an eye-tracking device to track the clinician's eye movements during the breast cancer diagnosis.

Dividing the activity session into three distinct phases (**PhaN.**, where N . is the n th number of a limited series, $n \in \mathbb{N} \forall N = \{1, \dots, 10\}$) per each three activities representing two different scenarios: *Multi-Modality (Sce1.)* vs *Assistant (Sce2.)*. The first two phases took place on an early stage of the *User Tests*, while we were focus to publish the results on a near future. The third phase, will cover the hereby *User Testing Guide*. Still, we will describe, as follows, the overall of the three phases to give higher contextualization.

Each scenario (**SceM.**, where M . is the m th number of a limited series, $m \in \mathbb{N} \forall M = \{1, 2\}$) will have three random patients (*i.e.*, **Pat1.**, **Pat2.** or **Pat3.**) from a set of 50 total number of patients. For each patient (**PatP.**, where P . is the p th number of a limited series, $p \in \mathbb{N} \forall P = \{1, 2, 3\}$), we will choose it from the total set of patients randomly. We do it as follows, let R be a random variable (**Rdm**) following the discrete uniform distribution as $r_1, r_2, r_3 \in \mathbb{N} \forall R = \{1, \dots, 50\}$. While $\text{Pat1.} = \text{Rdm}_{r_1} \wedge \text{Pat2.} = \text{Rdm}_{r_2} \wedge \text{Pat3.} = \text{Rdm}_{r_3}$ as soon as $r_1 \neq r_2 \neq r_3$ is *True*. In both two scenarios, *i.e.*, *Multi-Modality (Sce1.)* and *Assistant (Sce2.)*, by supporting our traditional devices, the interaction is made with mouse and keyboard.

Describing each phase, the first phase is nominated as **Pha1. User Characterization.** It is the Demographic Questionnaire, supporting our several characterizations of the clinician profile. For the major number of clinicians, this phase was committed on an early stage, as stated above. The **Pha1.** phase has three activities (**ActA.**, where A . is the a th number of a limited series, $a \in \mathbb{N}$) which are described as follows. The first activity, named as **Act1. Consent Form**, serves the purpose of providing participants information about privacy of the data and accept to proceed the test. The second activity, named as **Act2. Study Introduction**, serves the purpose of giving participants project contextualization and task awareness. Last but not least, the third activity of **Pha1.** phase, called as **Act3. Demographic Questionnaires**, is where participants fill the survey regarding their characterization as a user.

The second phase, nominated as **Pha2. Improving Visualization**, is also related with our later User Test Evaluations, corresponding to the tests done for the *Multi-Modality (Sce1.)* scenario. At this **Pha2.** we divided it into two activities: (1) **Act4. First Scenario Introduction** activity; and (2) **Act5. First Scenario Evaluation** activity. The first **Act4.** activity, aims at providing participants information about what *tasks* they will do. Each *task* represents the diagnostic of each patient, while we named it as **Act5. First Scenario Evaluation** activity.

Finally, and most importantly, the third phase, nominated as **Pha3. Assistant Establishment** phase, is where clinicians proceed for the diagnosis of the respective three, *i.e.*, **Pat1.**, **Pat2.** and **Pat3.**, patients. Clinicians will classify each patient by using the BIRADS [2]. On this phase, we will do several small questionnaires at the end of each scenario using NASA-TLX [22], System Usability Scale (SUS) [21] and measuring the BIRADS [2]. It is here, where we will also verify if our proposed designs impact [1, 17] on user expectations as intended, specifically as outlined by our several *Hypotheses* (Section 7) for the respective *Research Questions* (Section 7). We did it in regard to the novel introduction of an *AI-Assisted* system. On this phase, we will measure the participants expectations concerning the *AI-Assisted* system that we called **Act7. Second Scenario User Expectations** activity. The next **Act8. Second Scenario Introduction** activity, will be the introductory information about *AI-Assisted* system and what feature are covered by the system. The **Act9. Second Scenario Evaluation** activity represents the diagnostic of each patient (same as the **Act5.** activity), but this time with support of our novel *AI-Assisted* recommendations and explainability. And finally, the **Act10. Post-task Second Scenario Questions** activity will be a set of *post-task* questions.

For the user tests we used a three distinct prototype repositories, *i.e.*, the prototype-multi-modality repository, the prototype-multi-modality-assistant repository and the prototype-heatmap repository. The three are similar mirrors of the prototype-breast-cancer with major changes. The first repository, *i.e.*, the prototype-multi-modality repository, aims at providing clinicians a *Multi-Modality* strategy view. The *Multi-Modality* view, gives clinicians the possibility for the visualizing three modalities: (i) MammoGraphy (MG), both CranioCaudal (CC) and MedioLateral Oblique (MLO) views; UltraSound (US); and Magnetic Resonance Imaging (MRI). This view corresponds to the **Sce1.** scenario of both **Act4.** and **Act5.** activities at the **Pha2.** phase. The second and third repositories, *i.e.*, the prototype-multi-modality-assistant repository and the prototype-heatmap repository, aims at providing clinicians a recommendation system regarding our *AI-Assistive* techniques. Those techniques, will provide clinicians a twofold: (a) the opportunity of receive automatic recommendations concerning breast severities (BIRADS) of the patients; and (b) giving clinicians explainability (XAI) [12, 13] of those results. The automatic recommendations will be covered by the prototype-multi-modality-assistant repository, while the explainability will be covered by the prototype-heatmap repository. Both techniques are corresponding to the **Sce2.** scenario of **Act7., Act8., Act9.** and **Act10.** activities at the **Pha3.** phase.

2 Description

To verify our work, we identified measurable and explicit targets. By having several goals, including that a value percentage of the users should be able to operate the tasks without the need of help. On the same rate value, the user should be able to start and complete the medical diagnosis tasks over the system with little errors or mitigating those errors. Measuring the expected number of errors with a relation between our laboratory pilot tests. On the laboratory pilot tests we aim to test our prototypes with researchers. The Researchers are in the context of the system and know well the functionalities so that we need to expect a percentage value over their results compared to clinicians and not the same benefits. Last but not least, both users (researchers and clinicians) should be able to understand in a similar time amount the meaning of all visible controls. By the similar amount of time, it is expected to have a variance of the percentage value between researchers and clinicians of the same value percentage of the early goals described in this paragraph.

We tested each objective in early laboratory and field tests so that we could take the appropriate corrective actions. Also, we expect to run early field tests with researchers and clinicians to highlight issues that we overlooked and ignored during the prototyping phase. To support interaction use by the clinicians, we will try to emphasise several key factors on our user tests. The tasks must be simple, low intrusive, support for natural interaction and the system must always give visibility and the task current-state.

2.1 Devices

Traditional interaction remains the most common way to interact with user interfaces in a clinical environment. Unfortunately, most of this interaction is made by low profile equipment that makes users produce more errors and take more time interacting with those user interfaces.

On Figure 1 the user can select the list of patients. The list has a table with several patient information. The first column is the *Patient ID*; we used it as an identifier of the patient. That way we can have anonymised information with no reference to the patient name. The second column is the *Study Date*, the third column is the *Modality* of the used **DICOM** image, the fourth column is the *Study Description* of the used study and the last column is the number of *Images*.



The screenshot shows a software interface titled "MIMBCD-UI". At the top, there are icons for file operations (New, Open, Save, Print, Exit) and help (Help, About). Below the title bar is a menu labeled "Study List". The main area contains a table with the following data:

Patient ID	Study Date	Modality	Study Description	# Images
202732	20180309	MAMA^ROTINA	MAMA^ROTINA	2877
440624	20180314	01	01	8
737037	20180308	Breast	Breast	1
22586	20180314	01	01	8
866141	20180314	Breast	Breast	1
586890	20161012	Breast	Breast	1
590463	20180315	Breast	Breast	1
570100	20180314	Breast	Breast	1

In the bottom right corner, there is a small icon labeled "Feedback".

Figure 1: List of Patients.

As we can see in Figure 2, it shows the first task in our User Interface (UI), where the patient's breasts are on a small left column. The options are in a short row near of the viewport and described below. We also have the tabs where the user can change the patient. The centre viewport shows the **DICOM** image, and it can be configured to display a number up to four **DICOM** images at the same time. The viewport has some text information on it (yellow) with the details of the metadata. Nevertheless, the **Assistant** suggestions are shown on the top-right corner of the system.

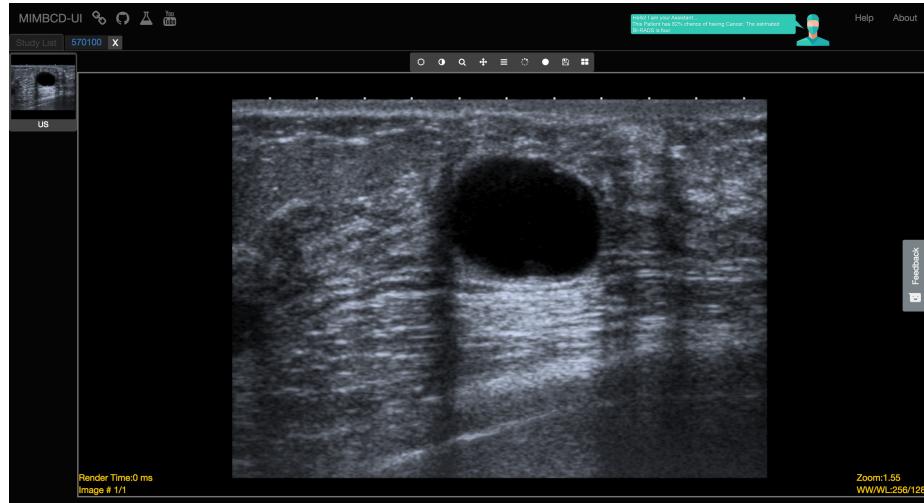


Figure 2: Viewer of the **DICOM** images.

Manual annotation is adopted by us thanks to Freehand ROI and Probe annotation features, both from CornerstoneJS. According to the CornerstoneJS Library, the user can create an annotation by setting up consecutive landmarks around a Region of Interest (ROI). The markers finish a lesion annotation when it interconnects the historical. Additional features available in our User Interface (UI) includes on-demand increment of the number of landmarks, and throw transformations of the shape of an annotation.

2.2 User Interactions

The systems have several buttons (Figure 3) that allows the user to interact or access to a set of user interface features. Each item of the following list represents each metaphoric icon of Figure 3.



Figure 3: Toolbar of the System available features.

The buttons are (from left to right of Figure 3) as follows:

- WW/WC
- Invert
- Zoom
- Pan
- Stack Scroll
- Freehand
- Probe
- Save
- Window Controller

2.3 Evaluation

Introduction of AI **Assistant** agents are significant factors which can naturally affect the performance of a medical workflow. While some prior studies [3, 4, 5] have investigated the functionality of healthcare systems, the *AI-Assisted* acceptability has mostly been overlooked in the existing Health Informatics (HI) literature regarding a Human-Computer Interaction (HCI).

The following Table 1 is presenting seven evaluation questions to have in mind during evaluation. The purpose of this questions is to facilitate systematic user studies regarding our novel **Assistant** in a clinical environment and support user stimulation for the introduction of *AI-Assisted* methods. The proposed issues involve various aspects of workflow combined with either need for satisfaction or division of attention.

Number	Issues of Content & Key Questions
1	How would the user describe the potential adoption of <i>AI-Assisted</i> methods on the Health Institution?
2	What are the user oppositions for <i>AI-Assisted</i> methods?
3	What examples of <i>AI-Assisted</i> methods does the user know regarding the Health Institution?
4	What are the obstacles of the user's Health Institution?
5	What is more important for the <i>AI-Assisted</i> information, the BIRADS or Pathology?
6	Is it important for the user to have the feature of Approve, Reject and Justify options?
7	For the user's opinion, what are the aspects that influence the decision?

Table 1: Usability Evaluation Questions

The influence of *AI-Assisted* [11] is an important variable for our empirical analysis. In fact, the trust of the user increases when the user perceived that the **Assistant** is giving the right inputs and that there will be a consequent increase of the clinician trust in our system.

The first question, the *How would the user describe the potential adoption of AI-Assisted methods on the Health Institution?* question. For the second question, the *What are the user oppositions for AI-Assisted methods?* question, we aim to understand what are the user constraints regarding an AI adoption on the user's current workflow. Third, we intend to filter possible examples of the clinical applications of AI on the Health Institutions by asking *What examples of AI-Assisted methods does the user know regarding the Health Institution?* directly to the clinician. The fourth question, underlines the reasons why several obstacles are present on the Health Institution, with the question *What are the obstacles of the user's Health Institution?* we can understand the challenges of achieving those issues and what are the solutions for surpass it. On the fifth question, where we ask *What is more important for the AI-Assisted information, the BIRADS or Pathology?*, we aim to understand what is more important for the user, the BIRADS or the Pathology [18] of the patient [8]. Almost last, the six question, where we ask for *Is it important for the user to have the feature of Approve, Reject and Justify options?* is an important question to understand the feature needs and options. Last but not least, the seven question, *For the user's opinion, what are the aspects that influence the decision?*, is where we will understand what is the most important information to show to the clinicians, therefore, we can more effectively and efficiently give more accurate information to the users.

To conclude this section, by doing this questions, we aim to support our user studies by giving our users, the clinicians, the opportunity of improving our empirical analysis regarding user's *open answers*. However, the results should be treated with caution. Several bias exists since we are doing here an ambiguous approach.

3 Methodology

The hereby prototype used is the v1.0.1-alpha version of our prototype-multi-modality-assistant. The purpose of this prototype is to involve an *AI-Assisted* tool (**Assistant**) for medical imaging at a breast screening diagnosis level. This **Assistant** was created with a front-end and bak-end architecture utilising common programming languages, libraries, frameworks and tools including JavaScript (JS) [10], NodeJS [29], HammerJS, CornerstoneJS [14] and Orthanc [15]. For the Machine Learning (ML) and Deep Learning (DL) [23, 24] component we will use several MATLAB technologies [27], promoting and feeding our Convolutional Neural Networks (CNN) [6] and Deep Reinforcement Learning (DRL) [19] techniques. Other central component of this prototype is a web-based PACS [7] pairwise with ubicous web technologies and based on the **Open Source (OS)** CornerstoneJS library [9, 14].

3.1 Environments

This section describes the user environment over interaction, the so called **Radiology Room (RR)** (Figure 4). This guide is based on soft-copy diagnosis using computer workstations in their current reading room environment. It will be here where we take impressions regarding the efficacy of radiologists, and their recommendations based on their experience for improvements on the soft-copy reading environment. Several studies demonstrated [28] that radiologist fatigue levels and performance are related to environmental factors such as number of false-negative and false-positives in addition to workstation enhancements. Supported by this guide, our research aims to conduct an investigation for the several environmental variables and improvements regarding the potentially enhancement that an *AI-Assisted* diagnosis could take in the **RR**. We expect to analyse the needed information and best solution to improve the workstation results.

3.2 Case Studies

The functionality of the prototype will be best demonstrated by a series of case studies. By describing the expected workflow and capabilities of the research study at the **RR** specific environment and changes of the workflow by using our system prototype. The study implies the evaluation of medical imaging *AI-Assisted* features on several breast lesions. The primary goal of this case studies analysis is to generate a receiver operating characteristic to evaluate the performance and validation of our **Assistant**. Let us consider a list of hypothetical use cases for the research investigation that evaluates the interaction and usability performance of the **Assistant**. Therefore, the following list will show the preliminary case studies.



Figure 4: Radiology Room

List of case studies to analyse our solution prototype:

- Multi-Modality *AI-Assisted* of a Breast Cancer Diagnosis;
- Priority & Minimal Information Visualisation;
- Performance & Response Measurement Values Acquisition;
- Radiologist Validation;

We expect to demonstrate several uses through a series of case studies, including implementation of our research prototype using an *AI-Assisted* technique and features for several view studies and other imaging research, as well as creation of a novel **Assistant** for the purpose. By creating a set of questions, we will try to achieve and feed this case studies. It is automatically associated with all cases. The radiologist may interact with our **Assistant** while manipulating the medical imaging and report to us difficulties and improvements. The number of questions is not restricted to the present document, since the interview will be open and suggestive [16]. There is no limit to the number of questions that can be asked per case but it should fit the amount of expected time per each.

The data will be collect from the study video and observations into a spreadsheet for further analysis. We will report the results of this tests and conclusions. This guide and respective use cases will be iteratively improved.

4 Roles

5 Material

For the material and apparatus, it is essential to capture the session apprehending the user interactions. In our case, we will record this interaction by using the QuickTime Player Version 10.4 (928.5.1) to obtain all interactions. We will pair this video tool with a user watch tool called Hotjar. This tool serves the purpose of using several logs of the interaction and gives us visualisation over it. Both instruments will help us to capture where are users interacting. By looking at the test participant's reactions, we find a lot of information regarding the prototype design.

The tools that we choose for the material and apparatus of this User Testing Guide are low-cost and easy to use. Our equipment is a cost-effective and, by using our laboratory materials, bringing it to the radiology room, we enable to capture not only what the user is doing on the screen, but on the body language supported by the interviews and observation.

The material used in the test sessions for the user interface consists of:

- MacBook Pro: it will allow the user to interact with the keyboard and a wireless mouse;
- Wireless Mouse: it will allow the user to interact with a mouse and will complement the keyboard;

5.1 Technical Details

To produce this traditional environment, and since we can simulate with a laptop, the mouse and keyboard interaction, we are using a Microsoft Mobile Mouse 4000 together with the MacBook Pro (Retina, 13-inch, Early 2015) with a standard integrated keyboard on the laptop.

5.2 Software

To track our user interactions across our system, we are using Hotjar. This tool is an analytic package allowing us to follow our users remotely. It also provides two critical pieces of functionality, among others, that can aid in remote user testing. First of all, the heatmaps allow us to see where users are clicking, tapping and scrolling on our system. Second, it records a video playback of the entire user session. The tool shows evidence of being useful for our studies while we successfully used it in the past.

To record the task activities and the interview, we used QuickTime [25]. The QuickTime (Apple Computer) tool is available for MacBook Pro to movie, audio and screen recording. Despite of have an overall of features, we just used it for our user's screen recording. It provides this functionalities at minimum requirements and compatible to our apparatus.

6 Tasks

During our user tests, we need to ask participants to provide a subjective assessment of their experience using our **Assistant**. There are several widely used questionnaires giving us different pros-and-cons. However, in most cases, a single question instrument [26] is the right method for a quantitative usability testing. By taking less time and effort to answer, participants are pursuing to this phase after task while it is minimally disruptive.

We will try to understand if, with the *AI-Assisted* techniques, the clinicians will encounter the most accurate severity (BIRADS) of the breast lesions [20] and patient's prognostic. For this purpose, we have three patients (Figure 5); each patient has three images in the respective modalities: (i) MG; (ii) US; and (iii) MRI. The clinicians will proceed to the activity of diagnosing the three patients within the support of our **Assistant** by the observation of ALL images.

In our **User Testing Guide** a set of tasks is necessary and carefully crafted. Our test studies involve asking participants to perform a set of tasks. By looking at what our user need to do with our system, our tasks are realistic as possible. We are not describing the exact steps participants need to take. We achieve that by avoiding the precise language used as labels in our system. The tasks are emotionally neutrals. And we did several pilot tests to prevent misleading situations saving us from wasting resources by accidentally use a lousy task or from getting bad data. The tasks are as follows.

List of stand alone tasks:

Task 1.1: Classify *Patient 1* on the **Assistant**;

Task 1.2: Classify *Patient 2* on the **Assistant**;

Task 1.3: Classify *Patient 3* on the **Assistant**;

Task 2.1: Freely explore *Patient 1* on the **Assistant**;

Task 2.2: Freely explore *Patient 2* on the **Assistant**;

Task 2.3: Freely explore *Patient 3* on the **Assistant**;

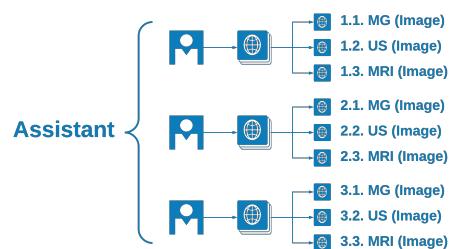


Figure 5: Diagram representing the use of the **Assistant** by clinicians.

7 Evaluation

8 Metrics

9 Goals

The next sections will describe the goals for prototype-multi-modality-assistant expectations. We will try to assess performance-related metrics such as time and correctness of participants completing *tasks* for our expectations. Our expectations are based of the results obtained at the lab as pilot tests.

9.1 Completion Rate

Completion Rate is the percentage of test participants who successfully complete the task without critical errors. A critical error is defined as an error that results in an incorrect or incomplete outcome. In other words, the completion rate represents the percentage of participants who, when they are finished with the specified task, have an "output" that is correct.

A Completion Rate of 90% is the goal for each task in this usability test.

Note: If a participant requires assistance in order to achieve a correct output then the task will be scored as a critical error and the overall completion rate for the task will be affected.

9.2 Error-Free Rate

Error-Free Rate is the percentage of test participants who complete the task without any errors (critical or non-critical errors). A non-critical error is an error that would not have an impact on the final output of the task but would result in the task being completed less efficiently.

An Error-Free Rate of 80% is the goal for each task in this tests.

9.3 Time on Task (ToT)

The time to complete a scenario is referred to as "Time on Task" (ToT). It is measured from the time the participant begins the scenario to the time which the participant signals completion.

9.4 Subjective Measures

Subjective opinions about specific tasks, time to perform each task, features, and functionality will be surveyed. At the end of the test, participants will rate their satisfaction with the overall system. Combined with the interview/debriefing session, these data are used to assess attitudes of the participants.

10 Problems

11 Results

A Test Report will be provided at the end of this tests. It will consist of a report and/or a presentation of the results; evaluation of the metrics against the pre-approved goals, subjective evaluations, and specific issues of the system, as well as, recommendations for resolution. The recommendations will be categorically sized by development to aid in implementation strategy. The results will be translated to a spreadsheet (view only). Also, more related information can be found at Test 4: Assistant.

12 Acknowledgements

References

- [1] Saleema Amershi, Dan Weld, Mihaela Vorvoreanu, Adam Fourney, Besmira Nushi, Penny Collisson, Jina Suh, Shamsi Iqbal, Paul N Bennett, Kori Inkpen, et al. Guidelines for human-ai interaction. 2019.
- [2] Corinne Balleyguier, Salma Ayadi, Kim Van Nguyen, Daniel Vanel, Clarisse Dromain, and Robert Sigal. Birads classification in mammography. *European journal of radiology*, 61(2):192–194, 2007.
- [3] Francisco M. Calisto, Alfredo Ferreira, Jacinto C. Nascimento, and Daniel Gonçalves. Towards touch-based medical image diagnosis annotation. In *Proceedings of the 2017 ACM International Conference on Interactive Surfaces and Spaces*, ISS ’17, pages 390–395, New York, NY, USA, 2017. ACM.
- [4] Francisco M Calisto, Pedro Miraldo, Nuno Nunes, and Jacinto C Nascimento. Breastscreening: A multimodality diagnostic assistant.
- [5] Francisco Maria Calisto. Medical imaging multimodality breast cancer diagnosis user interface. Master’s thesis, Instituto Superior Técnico, Avenida Rovisco Pais 1, 1049-001 Lisboa - Portugal (EU), 10 2017. A Medical Imaging for Multimodality of Breast Cancer Diagnosis by an User Interface.
- [6] Gustavo Carneiro, Jacinto Nascimento, and Andrew P Bradley. Unregistered multiview mammogram analysis with pre-trained deep learning models. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 652–660. Springer, 2015.
- [7] Robert E Cooke Jr, Michael G Gaeta, Dean M Kaufman, and John G Henrici. Picture archiving and communication system, June 3 2003. US Patent 6,574,629.
- [8] Eda Elverici, Ayşe Nurdan Barça, Hafize Aktaş, Arzu Özsoy, Betül Zengin, Mehtap Çavuşoğlu, and Levent Araz. Nonpalpable bi-rads 4 breast lesions: sonographic findings and pathology correlation. *Diagnostic and Interventional Radiology*, 21(3):189, 2015.
- [9] Joseph Feller, Brian Fitzgerald, et al. *Understanding open source software development*. Addison-Wesley London, 2002.
- [10] David Flanagan. *JavaScript: the definitive guide.* ” O'Reilly Media, Inc.”, 2006.
- [11] Ian Goodfellow, Yoshua Bengio, Aaron Courville, and Yoshua Bengio. *Deep learning*, volume 1. MIT press Cambridge, 2016.
- [12] David Gunning. Explainable artificial intelligence (xai). *Defense Advanced Research Projects Agency (DARPA)*, nd Web, 2017.

- [13] Andreas Holzinger, Chris Biemann, Constantinos S Pattichis, and Douglas B Kell. What do we need to build explainable ai systems for the medical domain? *arXiv preprint arXiv:1712.09923*, 2017.
- [14] Jason Hostetter, Nishanth Khanna, and Jacob C Mandell. Integration of a zero-footprint cloud-based picture archiving and communication system with customizable forms for radiology research and education. *Academic radiology*, 2018.
- [15] S. Jodogne, C. Bernard, M. Devillers, E. Lenaerts, and P. Coucke. Orthanc – A lightweight, RESTful DICOM server for healthcare and medical research. In *Biomedical Imaging (ISBI), IEEE 10th International Symposium on*, pages 190–193, San Francisco, CA, USA, April 2013.
- [16] Ger Joyce, Mariana Lilley, Trevor Barker, and Amanda Jefferies. From healthcare to human-computer interaction: Using framework analysis within qualitative inquiry. In *International Conference on Applied Human Factors and Ergonomics*, pages 93–100. Springer, 2017.
- [17] Rafal Kocielnik, Saleema Amershi, and Paul N Bennett. Will you accept an imperfect ai? exploring designs for adjusting end-user expectations of ai systems. 2019.
- [18] Gabriel Maicas, Andrew P Bradley, Jacinto C Nascimento, Ian Reid, and Gustavo Carneiro. Pre and post-hoc diagnosis and interpretation of malignancy from breast dce-mri. *arXiv preprint arXiv:1809.09404*, 2018.
- [19] Gabriel Maicas, Gustavo Carneiro, Andrew P Bradley, Jacinto C Nascimento, and Ian Reid. Deep reinforcement learning for active breast lesion detection from dce-mri. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 665–673. Springer, 2017.
- [20] American College of Radiology. BI-RADS Committee. *Breast imaging reporting and data system*. American College of Radiology, 1998.
- [21] Konstantina Orfanou, Nikolaos Tselios, and Christos Katsanos. Perceived usability evaluation of learning management systems: Empirical evaluation of the system usability scale. *The International Review of Research in Open and Distributed Learning*, 16(2), 2015.
- [22] Anjana Ramkumar, Pieter Jan Stappers, Wiro J Niessen, Sonja Adebarh, Tanja Schimek-Jasch, Ursula Nestle, and Yu Song. Using goms and nasa-tlx to evaluate human–computer interaction process in interactive segmentation. *International Journal of Human–Computer Interaction*, 33(2):123–134, 2017.
- [23] David Ribeiro, André Mateus, Pedro Miraldo, and Jacinto C Nascimento. A real-time deep learning pedestrian detector for robot navigation. In

Autonomous Robot Systems and Competitions (ICARSC), 2017 IEEE International Conference on, pages 165–171. IEEE, 2017.

- [24] David Ribeiro, Andre Mateus, Jacinto C Nascimento, and Pedro Miraldo. A real-time pedestrian detector using deep learning for human-aware navigation. *arXiv preprint arXiv:1607.04441*, 2016.
- [25] Melissa R Rowell, Frank M Corl, Pamela T Johnson, and Elliot K Fishman. Internet-based dissemination of educational audiocasts: a primer in podcasting-how to do it. *American Journal of Roentgenology*, 186(6):1792–1796, 2006.
- [26] J Sauro. 10 things to know about the single ease question (seq). *Measuring U*, 2012, 2012.
- [27] Andrea Vedaldi and Karel Lenc. Matconvnet: Convolutional neural networks for matlab. In *Proceedings of the 23rd ACM international conference on Multimedia*, pages 689–692. ACM, 2015.
- [28] Stephen Waite, Srinivas Kolla, Jean Jeudy, Alan Legasto, Stephen L Macknik, Susana Martinez-Conde, Elizabeth A Krupinski, and Deborah L Reede. Tired in the reading room: the influence of fatigue in radiology. *Journal of the American College of Radiology*, 14(2):191–197, 2017.
- [29] Jim Wilson. *Node.js 8 the Right Way: Practical, Server-side Javascript that Scales*. Pragmatic Bookshelf, 2018.