Medical Imaging Diagnosis Assistant: AI-Assisted Radiomics Framework User Validation

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INTRODUCTION

Artificial Intelligence has the potential to alter many application domains fundamentally. One prominent example is clinical radiology. The literature hypothesizes that Deep Learning algorithms will profoundly affect the clinical workflow. In this work, we utilized the unprecedented opportunity presented by developing Radiomics to investigate how a *Multi-Modality* Framework and AI could add value in the Medical Imaging (MI) chain, including improvements of workflow

GOALS

Our work is targeted for the following main goals:

- Protocol and guidelines to the introduction of an *AI-Assisted* Framework;
- Compare current and novel *AI-Assisted* approach;
- Use an eye-tracking device during patient diagnosis;
- Introduction of Machine Learning (ML) and Deep Reenforcement Learning (DRL) in a *Multi-Modality* framework;
- Promote the introduction of DenseNet and Convolutional Neural Networks (CNN) techniques (MAICAS et al., 2017);

A vital component of this research will be the access to a significant number of clinical settings and radiologists (FRANCISCO, 2017; CALISTO, F. M., 2019). Other central component of our framework is a distributed-based PACS pairwise with ubicous web technologies and based on *Open Source (OS)* libraries.

List of used technologies that support our work:

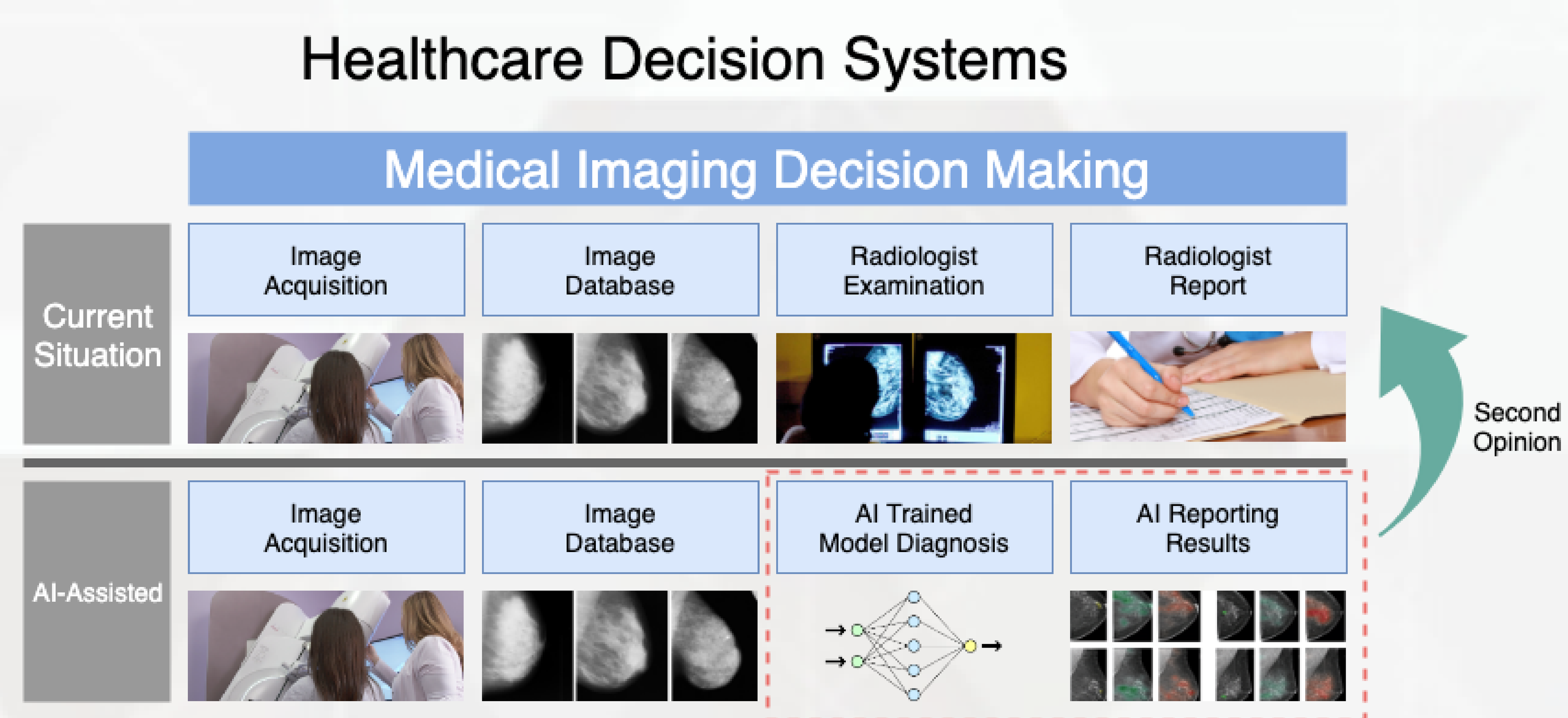
1. NodeJS;
2. CornerstoneJS (HOSTETTER; KHANNA; MANDELL, 2018);
3. Orthanc (JODOGNE et al., 2013);

METHODOLOGY

Our methodology will be as follows:

- Participants will take part in the tests at our formed institution protocols (*e.g.*, HFF);
- The validation of the framework will take place in a typical *Radiology Room (RR)* environment and workflow (Figure 1);
- Note takers and data logger(s) will monitor the sessions for observation in the *RR*;

Figure 1 – Artificial Intelligence (AI) supporting the Medical Imaging (MI) current situation with decision making as a second opinion to Radiologists. Starting at the image acquisition from each patient, to the phase of putting those images on a patient database. From there, Radiologists can examine each image and writing a final report. At this point, researchers can add a second opinion to support the medical decision with trained models of AI and autonomous reporting of the results.



Source: Francisco Calisto (2019).

We propose and measure a second opinion in regard to the current *RR* situation (CALISTO, F. M., 2019). The second opinion will take advantage of our AI trained models (*Assistant*), as well as it reporting results. To measure efficiency and efficacy of our *Assistant* we will use a set of scales. The scales are: (1) NASA-TLX; (2) SUS; and (3) DOTS.

FRAMEWORK

The next Figures 2, 3 e 4 are samples of our working framework:

Figure 2 – UI framework overview showing a patient's MI.

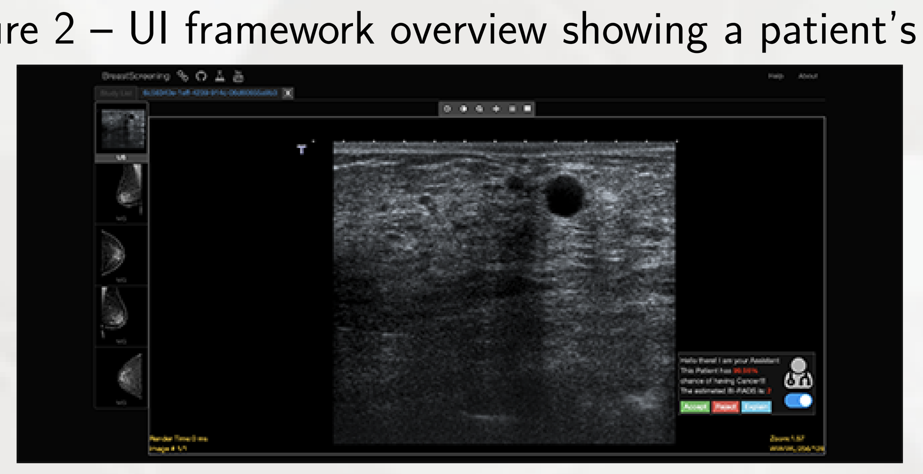


Figure 3 – The *AI-Assisted* oracle and interaction.

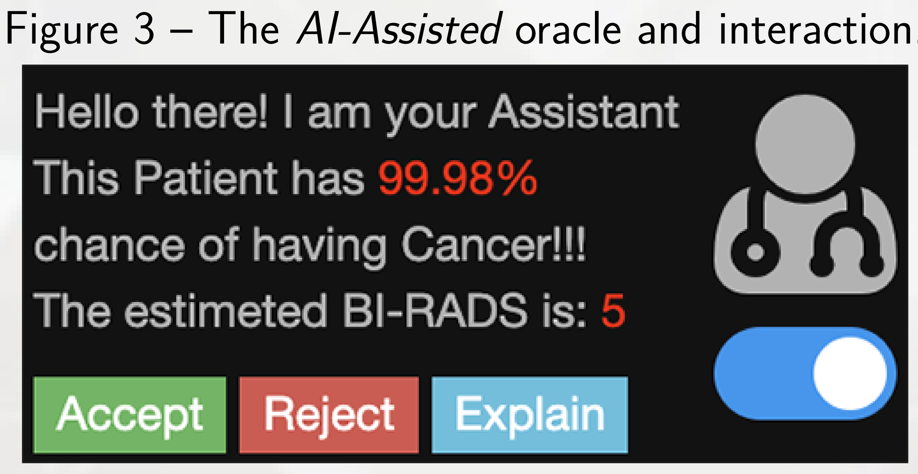
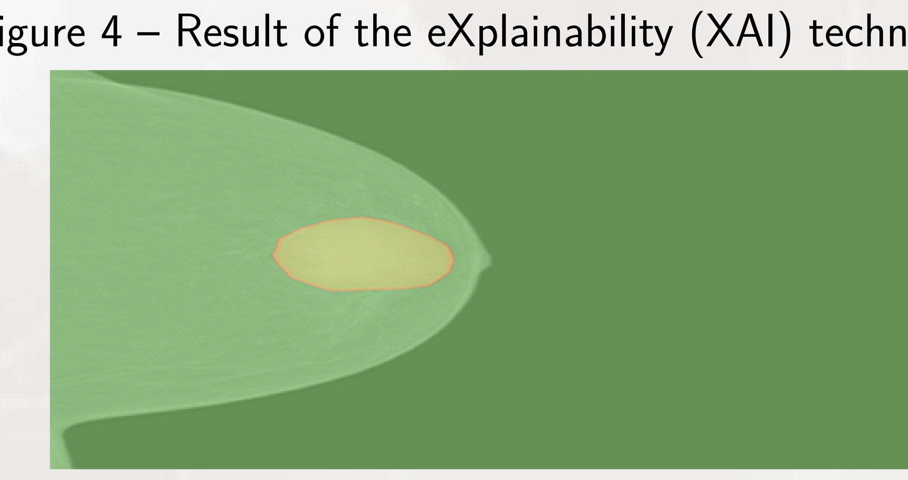


Figure 4 – Result of the eXplainability (XAI) techniques.



FUTURE WORK AND CONCLUSIONS

Our work is a first attempt to test the potential of Radiomics in a real-world clinical scenario. More than answering our research questions it opens a number of new avenues for further investigation. This research leverages on previous work implementing DL for active breast lesion detection. However, integrating the Framework on a pipeline requires a lot of engineering work. For effective clinical application, our work requires a proper clinical trial procedure which is out of the scope of this poster. Ultimately, we believe there is significant room for future research - to which this work is an important but only initial step - and we hope to see further exploration on the topic.

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