

# Using Co-Op Multi-Agent Reinforcement Learning for Cancerous Cell Detection in Mammograms

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**Abstract:** Breast cancer is one of the leading causes of mortality among women. Early and reliable detection of cancerous cells is paramount in cancer diagnosis and prognosis. Various machine learning approaches have been developed for detecting malignant cells in mammograms over the years. This paper will discuss the application of Co-Operative Multi-Agent Reinforcement Learning (MARL) in the detection of cancerous cells in annotated regions in mammograms. MARL has been shown to be an effective technique in solving decision making problems in the domain of reinforcement learning. MARL-based approaches have been used for image classification problems and produced promising results. Co-operative multi-agent systems have been developed, in which multiple agents iteratively scans different areas of an image and communicate their partial observations with neighboring agents, thus extracting features from the images and successfully classifying the image. This cooperation is the basis for the model's efficiency and fast convergence. In this paper, we attempt at developing a MARL model that can detect malignant regions in mammograms from the CBIS-DDSM dataset.

**Keywords:** breast cancer; image classification; reinforcement learning, mammogram, cancer detection, computer aided detection

## 1. Introduction

According to the World Health Organization, breast carcinoma is the most prevalent type of cancer in the world. Breast cancer was responsible for around 685,000 deaths in the year of 2020. Which is north of 24% of total 2.26 million new cases [9]. It is estimated that around 13% of women will develop breast cancer in their lifetime and 3% of these cases will result in death [8]. Therefore, early detection and treatment for breast cancer is paramount for reducing the fatality rate.

One of the most common screening techniques that is most effective in early detection of breast cancer are mammograms. Mammograms are low dose X-ray images of the breast where the density of tissue is visible and is used by radiologists to look for potential signs of cancer. Breast cancer detection from mammograms primarily is done manually by radiologists with training and experience in interpreting medical images of the breast. However, for the last 2 decades, machine learning has been explored as an automation of cancer screening. However, the primary challenge of detecting cancerous regions from mammograms is that the Region Of Interest (ROI) consists of a small portion of the whole mammogram. Therefore, most of the input data is irrelevant to the image classifier. To overcome this, a dataset with annotated ROI has been chosen for the effective and efficient training of the Reinforcement Learning model that we propose. The CBIS-DDSM [1] is a curated, decompressed and segmented subset of the Digital Database for Screening Mammography [2] in which the ROIs are annotated by professional mammographers as seen in Fig 1.

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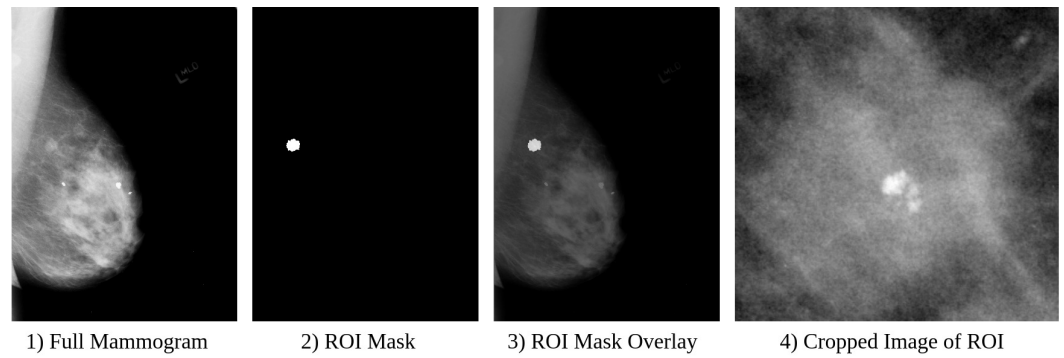
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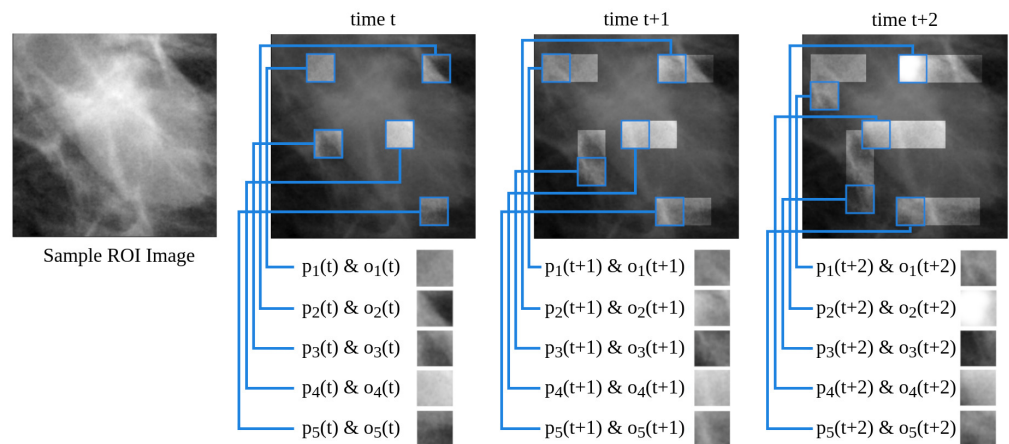
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**Figure 1.** ROI annotations in CBIS-DDSM. (1) represents the original mammogram image. (2) is the ROI mask specific to the original image. (3) shown an overlay of the ROI mask on the original, denoting where on the original image is the ROI. (4) is the ROI cropped out of the original

In this paper, we propose an approach that uses Deep Reinforcement Learning that utilizes multiple agents to take partial observations of ROI images, communicate findings with other agents and correctly classify the image as either Benign or Malignant. By formulating this problem as a Markov Decision Process, we propose this unsupervised method of intelligent agents working together to identify features from a mammogram image. In this context, the image is taken as an unknown environment which the agents must learn to traverse, obtain observations, communicate these observations to other agents, receive messages and form their own beliefs about the nature of the environment (as visualized in Fig 2). By setting the agents to maximize a discounted reward, we motivate them to learn a policy to optimally traverse the environment and communicate its findings.



**Figure 2.** Each agent  $a_i$  at time  $t$  has a position on the image  $p_i(t)$  and extracts features from its partial observation  $o_i(t)$  and afterwards, repositions itself to make the next observation.

The rest of this paper is organized as follows. Section 2 reviews the existing literature in RL, DRL, Multi-Agent RL and machine learning methods of breast cancer detection from mammograms. Section 3 details the mechanism of our proposed model. Section 4 assesses the performance of the model and present experimental results. Section 5 discusses the findings and finally, the article is concluded in section 6.

## 2. Literature Review

Over the years, many CAD methods have been used for the task of detecting breast cancer from mammogram images. The approaches can be broadly classified into X categories:

2.1. Machine Learning55

Vanilla machine learning is one of the earliest and most broadly used techniques in image classification. There have also been a number of specialized methods of breast cancer detection in mammograms using machine learning. Borges [4] was among the first to compare machine learning methods on mammogram classification where Bayesian Networks outperformed J48 on the WBCD [5] dataset. Assiri et al. reviewed an ensemble of different machine learning algorithms (SVMs, Decision Trees etc.) and found that the Simple Logistic Regression model achieved the highest F3 score on the same dataset [6] Avci et al. explored mammogram image enhancement, ROI detection and classification on the mini-MIAS dataset to compare performances of different combinations of pre-processing techniques [3]

2.2. Deep Learning66

Deep learning refers to a subset of machine learning techniques that utilize artificial neural networks with many hidden layers, which enable the modeling of complex relationships and representations in large datasets for various tasks such as classification, regression, and generation. A combined DL and ML approach was shown to substantially improve performance compared to a single model on 731 mammogram images of 357 women and their other clinical data to find correlations (using ML) between cancer diagnosis (using DL) result and clinical variables [7].

=====end=====64

2.3. Deep Reinforcement Learning75

3. Materials and Methods76

Materials and Methods should be described with sufficient details to allow others to replicate and build on published results. Please note that publication of your manuscript implicates that you must make all materials, data, computer code, and protocols associated with the publication available to readers. Please disclose at the submission stage any restrictions on the availability of materials or information. New methods and protocols should be described in detail while well-established methods can be briefly described and appropriately cited.

Research manuscripts reporting large datasets that are deposited in a publicly available database should specify where the data have been deposited and provide the relevant accession numbers. If the accession numbers have not yet been obtained at the time of submission, please state that they will be provided during review. They must be provided prior to publication.

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This is an example of a quote.92

4. Results93

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation as well as the experimental conclusions that can be drawn.96

4.1. Subsection97

4.1.1. Subsubsection98

Bulleted lists look like this:99

- First bullet;100
- Second bullet;101
- Third bullet.102

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2. Second item;

3. Third item.
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All figures and tables should be cited in the main text as Figure 3, Table 1, etc.

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This is the example 1 of equation:

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$$a = 1,$$

(1)

the text following an equation need not be a new paragraph. Please punctuate equations as regular text.

This is the example 2 of equation:

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$$a = b + c + d + e + f + g + h + i + j + k + l + m + n + o + p + q + r + s + t + u + v + w + x + y + z \quad (2)$$

Please punctuate equations as regular text. Theorem-type environments (including propositions, lemmas, corollaries etc.) can be formatted as follows:

**Theorem 1.** *Example text of a theorem.*

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## 6. Conclusions

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This section is not mandatory, but may be added if there are patents resulting from the work reported in this manuscript.

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**Abbreviations**

The following abbreviations are used in this manuscript:

MDPI	Multidisciplinary Digital Publishing Institute
DOAJ	Directory of open access journals
TLA	Three letter acronym
LD	Linear dichroism

**Appendix A**

*Appendix A.1*

The appendix is an optional section that can contain details and data supplemental to the main text—for example, explanations of experimental details that would disrupt the flow of the main text but nonetheless remain crucial to understanding and reproducing the research shown; figures of replicates for experiments of which representative data are shown in the main text can be added here if brief, or as Supplementary Data. Mathematical proofs of results not central to the paper can be added as an appendix.

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Entry 1	Data	Data
Entry 2	Data	Data

**Appendix B**

All appendix sections must be cited in the main text. In the appendices, Figures, Tables, etc. should be labeled, starting with “A”—e.g., Figure A1, Figure A2, etc.

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