Literature Review on Artificial Intelligence in Radiology

Comparison on Breast Cancer and Covid-19 CNN’s

Final Paper

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Introduction

Breast Cancer

Breast cancer is one of the most common and leading cancers affecting women worldwide. Early detection is still linked to a better prognosis, which has enhanced the importance of timely and improved screening methods (Ahmad, 2019). In the past, doctors had to manually mark the suspicious breast cancer location. Many studies have suggested that this manual process can be time-consuming (Ting et al., 2019). Furthermore, research shows that radiologists frequently struggle to categorize mammography mass lesions, which, according to Chougrad, results in, “unnecessary breast biopsies to assuage suspicions and adds exorbitant costs to an already burdened patient and health care system” (Chougrad et al., 2018). Therefore, to aid in the detection and management of breast cancer, medical practitioners use several classifiers and predictors for effective and quick patient diagnosis. The implementation of pattern recognition mechanisms combined within a Digital Pathology system could aid with this, as it, “aims to help the radiologist classify mammography mass lesions” (Chougrad et al., 2018).

Digital Pathology and Pattern Recognition

This is relevant to digital pathology as it is on the verge of becoming a mainstream option for routine diagnostics, marking a significant advancement in everyday clinical practice for diagnosing diseases and conditions (Nithya & Santhi, 2011). This is advancement in Digital pathology is possible due to the, “powerful machine learning algorithm[s] for pattern recognition, which ha[ve] become widespread thanks to high speed processors and graphics processing units” (Jacobson et al., 2018). Moreover, due to this advancement in pattern recognition algorithms there is an increase in the potential to support clinicians with early detection in Breast Cancer through routine mammograms.

Digital pathology is an area of study that involves digitally capturing and saving high-resolution photographs of pathology slides (Cruz-Roa et al., 2018). The fields of pathology and medical imaging have benefited greatly from the integration of digital pathology with AI and pattern recognition. Digital pathology images can be automatically analysed and interpreted using pattern recognition methods like deep learning and machine learning. To give more details, this specialised field called pattern recognition, uses computer algorithms to automatically detect patterns in data and is very helpful in the field of health care. Furthermore, it involves, “the detection of meaningful patterns and structures within the data, which are then leveraged to perform various actions, such as categorizing the data into distinct classes or categories” (Bishop, 2006).

AI in Relation to Pattern Recognition

AI algorithms have to ability to complete tasks in pattern recognition by recognizing patterns, features, and anomalies in the images, making it possible to diagnose many diseases accurately and quickly (Cruz-Roa et al., 2018). Machine learning and deep learning are the two main AI techniques used in radiology (Zhao, 2020).

Machine learning models are trained to apply mathematical techniques to find patterns in data and produce predictions, either under supervision or independently. In order to simulate extremely complicated interactions between inputs and outputs, deep learning is a subclass of machine learning that uses deep neural networks (Zhao, 2020). Additionally, manually derived features from photos with a texture resembling a tumour are used to train statistical machine learning models. Following training, they are able to categorise the conditions of patients in order to "support clinical decision making" (Hosny et al., 2018).

Pattern Recognition with Neural Networks in Pathology

Recently, there have been impressive advancements in the field of digital pathology and pattern recognition. Convolutional Neural Networks (CNNs) have taken over as the preferred technique for teaching computers to recognise and comprehend images (Cruz-Roa et al., 2018). Research has shown that, “a neural network, including latest convolutional and recurrent network, is a powerful machine learning algorithm for pattern recognition” (Jacobson et al., 2018). Additionally, CNNs have successfully completed tasks like tumour and mitosis detection in the field of pattern recognition, notably in pathology, showing their potential to revolutionise cancer diagnosis and therapy (Cruz-Roa et al., 2018).

What are Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a particular kind of deep learning architecture made specifically for processing and analysing visual data, including images (Cruz-Roa et al., 2018). Due to their ability of automatically learning hierarchical features from incoming images, CNNs are very good at tasks like image classification, object recognition, and segmentation. As a result, CNNs are frequently used in the healthcare sector for a variety of purposes, including their effectiveness in managing data from medical imaging and other tasks.

In this project two main Convolutional Neural Networks were used, they included Mask R-CNN and AlexNet. Mask R-CNN is an extension of the Faster R-CNN architecture (He et al., 2017). In contrast to Faster R-CNN, the main Mask R-CNN strategy has many more sub-strategies, including instance segmentation, bounding-box object detection, and person keypoint detection (He et al., 2017). The precise number of layers in a mask R-CNN depends on the implementation and particular requirements. On the other hand is AlexNet which is one of the most popular neural. AlexNet has five convolution layers, three pooling layers, and two fully connected layers with approximately 60 million free parameters (Ragab et al., 2019).

Research Problem

This research project was aimed to enhance breast cancer detection by leveraging a combination of AI technologies, including Convolutional Neural Networks, Pattern Recognition, Machine Learning and Deep Learning. Additionally, a comparative analysis was conducted, evaluating code from GitHub that focused on breast cancer and covid-19 detection using mammograms and x-rays.

Materials and Methodologies

There are two main parts to this research project, I will discuss both the parts in this section. First, I conducted an extensive literature review, and second, I carried out a comparative analysis of both sets of code.

Part 1- Literature Review

Firstly, the literature review was focused on finding resources that focused on predicting breast cancer using AI, pattern recognition and convolutional neural networks. This included evaluating and classifying research papers on breast cancer that were found on Web of Science and IEEE, resources provided by the University of Victoria library. As well as publicly available resources such as Zenodo and Github. Please refer to Figure 2 and Figure 3 for library resources. As well as Figure 1 and Figure 4 for publicly available resources. In order to complete this literature review, certain keywords were used to support in finding the best articles research papers. Some of these keywords included x-rays, mammograms, CT scans, pattern/image recognition, neural networks, deep learning, computer-aided analysis, artificial neural network, breast mass lesion classification, medical diagnostic imaging, etc. The overall purpose of the literature review is to provide a better understanding of how AI technology can be used to diagnose breast cancer. The literature review's secondary goal is to compile and assess the information obtained.

Figure 1: Research found through Zenodo

Article Number	Title	Database Available?	Found On	Equipment or Technology Used	Performance Meassures
#1	Detection and Classification of Breast Cancer using Artificial Intelligence Approaches	No	Zenodo	Breast cancer detection - using histopathological image - Provide accurate	F1-score, Recall, Accuracy, and Precision
#2	Analytical Estimation of Quantum Convolutional Neural Network and	No	Zenodo	Breast cancer detection on a quantum convolutional neural network algorithm	Time Complexity and Accuracy
#3	Deep learning for cancer tumor classification using transfer learning and feature	No	Zenodo	3 Difference Architectures	Accuracy
#4	Patient-Centric Reddit Cancer Dataset	Yes	Zenodo	Patient-Centric Reddit Cancer Dataset (PCRCD)	NA
#5	Data from: High-throughput adaptive sampling for whole-slide histopathology	Yes	Zenodo	Whole Slide Images & HASHI & CNN's & Adaptive gradient-based sampling algorithm	AUC, Dice, PPV, NPV, TPR, TNR, FPR, and false negative rate

Figure 2: Research found through Web of Science

Article Number	Title	Database Available?	Found On	Equipment or Technology Used	Performance Meassures
#6	Breast Cancer Statistics: Recent Trends	Yes	Web of Science	NA - Only for Statistics in Breast Cancer	NA
#7	Convolutional neural network improvement for breast cancer classification	No	Web of Science	Supervised learning, Artificial neural network, Image processing, Medical imaging,	21 Meassures used: Accuracy, Sensitivity, ROC, Specificity, etc .
#8	Deep Convolutional Neural Networks for breas t cancer screening	No	Web of Science	Computer-aided Diagnosis (CAD) system based on deep Convolutional Neural Networks (CNN	Accuracy, ROC, AUC,
#9	Representation learning for mammography mass lesion classification	No	Web of Science	deep learning techniques to automatically learn discriminative features avoiding the	ROC (AUC)
#10	Breast cancer detection using deep convolutional neural networks and support	Yes	Web of Science	Computer aided detection (CAD) system is proposed for classifying benign and malignant	SVM & AUC. Accuracy AUC Sensitivity Specificity Precision F1 score
#11	Detection and classification of normal and abnormal patterns in mammograms using	No	Web of Science	Four major steps, namely, image-preprocessing, segmentation, feature	f-measure and accuracy
#12	Breast cancer diagnosis from mammographic images using optimized feature selection	Yes	Web of Science	Breast cancer detection model - five major phases: preprocessing, segmentation, feature	accuracy, specificity, Precision, FPR, FNR, NPV, FDR, F1-score, and MCC

Figure 3: Research found through IEEE

Article Number	Title	Database Available?	Found On	Equipment or Technology Used	Performance Meassures
#13	Research on the Detection Method of Breast Cancer Deep Convolutional Neural Network Based on Computer Aid	No	IEEE	convolutional neural networks with different structures	AUC
#14	Breast Cancer classification using Neural networks	No	IEEE	DNN (deep neural network), CNN (Convolutional Neural Network) and ANN Artificial Neural Network) and RFE	Accuracy and Loss
#15	Deep Neural Networks Improve Radiologists' Performance in Breast Cancer Screening	Link to GitHub	IEEE	They have a git hub link to the models they used	ROC, PRAUC, AUC
#16	Breast Cancer Image Classification Using Deep Convolutional Neural Networks	No	IEEE	deep convolutional neural networks	accuracy, sensitivity, specificity, accuracy and recall
#17	A New Deep Convolutional Neural Network Model for Automated Breast Cancer Detection	No	IEEE	automated breast cancer prediction using deep learning techniques.	Accuracy, Area under the Receiver Operating Characteristic (ROC) Curve (AUC), the Classification Mean Absolute Error (MAE), Mean Squared Error (MSE) metrics.

Figure 4: Research found through GitHub

DataSet Number	Title	Database Available?	Found On	Technology / Keywords	Performance Meassures
#1	Breast-cancer-detection-and-diagnosis-CNNs	Yes	GitHub	Breast Cancer and convolutional Neural Networks	Accuracy and AUC
#2	Breast Cancer Tumor Classification	No	GitHub	Breast Cancer and convolutional Neural Networks	Keras , written in Python, enables fast experimentation
#3	CBIS DDSM Breast Cancer Mammography Dataset - Convolutional Neural Networks for classifying Abnormality Type and Benign/Malignant Diagnosis	Yes	GitHub	Convolutional Neural Networks	Not mentioned
#4	Breast-Cancer-Detection	No	GitHub	Convolutional Neural Networks	Not mentioned

Furthermore, lets see how many resources were discovered through each platform. Please refer to Figures 5 and 6, which show the number of resources accessible via library platforms and open access platforms, respectively. Only the highly cited papers were taken into consideration for the literature evaluation in accordance with the research approach for the library resources. On the other hand, the open access platforms did not have option to filter and find highly cited resources. The finest navigational environment and the most frequently cited resources were found on Web of Science. The most trustworthy source used for this literature review has also been web of science. On the other hand, IEEE is another excellent and trustworthy library resource that was employed in the literature review. This is due to IEEE's requirement that all conference papers undergo peer review before being published. For the initial stages of the research for this literature review, Zenodo was used. Due to the fact that Zenodo does not need peer review for all resources provided or have a set process to follow, it did not have many highly referenced publications. GitHub is the platform used to find datasets and reports with corresponding already tested coding. GitHub is a code hosting platform for version control and collaboration. It can be seen in the figures below, as we tightened the search parameters, GitHub's resources and code grew more condensed.

Figure 5: Resources found on Library Platforms

Library Plaforms		
Searched	**Web of Science Results**	**IEEE Results**
Breast Cancer	558	9,661
Breast Cancer & CNN's	5	664
Breast Cancer & CNN's & pattern Recognition	24	38
Breast Cancer & CNN's & deep learning	98	491

Figure 6: Resources found on Open Access Platforms

Open Access Plaforms		
Searched	**Zenodo Results**	**GitHub Results**
Breast Cancer	20212	18,348
Breast Cancer and convolutional Neural Networks	2009696	35
Breast Cancer and convolutional Neural Networks and pattern Recognition	2011907	0
Breast Cancer and convolutional Neural Networks and deep learning	2014959	7
Breast Cancer and convolutional Neural Networks and pattern Recognition and deep learning	2017105	0
Breast Cancer and convolutional Neural Networks and Image classification	2023979	9

After looking through all the articles and platforms I would like to discuss how my search approach enabled me to categorize the research papers (shown in the figures above) into tiers 1 through 10. For more information, see Figure 7. Some of the materials on library search engines like IEEE and Web of Science were linked to the code and data on GitHub. Library resources were used to locate research papers ranked one, five, and nine, although GitHub code was openly available. Majority of the research articles that were listed from one through ten on the ranking list came from Web of Science.

Figure 7: Ranked Resources

Rank	Title - As Shown on GitHub	Equipment used- As Shown on GitHub	Title - As Shown on Research Paper	Equipment used - As Shown on Research Paper	Resource Found on	Performance Meassures	Linkage between Paper and Code?
#1	Breast-cancer-detection-and-diagnosis-CNNs	BIS-DDSM (Curated Breast Imaging Subset of Digital Database for Screening Mammography)	Breast cancer detection using deep convolutional neural networks and support vector machines	A new computer aided detection (CAD) system is proposed for classifying benign and malignant mass tumors in breast mammography images	Web of Scince	SVM & AUC. Accuracy AUC Sensitivity Specificity Precision F1 score	Yes
#2	Classifying Tumors in Mammograms	Used 2 different mammogram datasets of differing sizes and built various neural network models in order to classify Tumors vs. No Tumors in mammogram images. Datasets: MIAS and CBIS-DDSM	Classifying Tumors in Mammograms	Using neural networks to identify tumors	GitHub	Accuracy and f1-score	Yes - Both through GitHub
#3	Not Linked to GitHub	Not Linked to GitHub	Convolutional neural network improvement for breast cancer classification	Supervised learning, Artificial neural network, Image processing, Medical imaging, Breast cancer classification,	Web of Scince	21 Meassures used: Accuracy, Sensitivity, ROC, Specificity, etc	NA
#4	Not Linked to GitHub	Not Linked to GitHub	Deep Convolutional Neural Networks for breast cancer sc reening	Computer-aided Diagnosis (CAD) system based on deep Convolutional Neural Networks (CNN	Web of Scince	Accuracy, ROC, AUC,	NA
#5	Breast-Cancer-Classification	A breast cancer classifier that can accurately classify a histology image as benign or malignant. Code provided in Python.	Detection and Classification of Breast Cancer using Artificial Intelligence Approaches	Breast cancer detection - using histopathological image - Provide accurate classification of Benign and Malignant tumors	Zenodo	F1-score, Recall, Accuracy, and Precision	No - From Separate Sources
#6	Deep Neural Networks Improve Radiologists' Performance in Breast Cancer Screening	A model which takes images as input (image-only) and a model which takes images and heatmaps as input (image-and-heatmaps).	Deep Neural Networks Improve Radiologists' Performance in Breast Cancer Screening	Deep convolutional neural network for breast cancer screening exam classification, trained, and evaluated on over 200000 exams.	IEEE	ROC, PRAUC, AUC	Yes
#7	Not Linked to GitHub	Not Linked to GitHub	Breast Cancer classification using Neural networks	DNN (deep neural network), CNN (Convolutional Neural Network) and ANN Artificial Neural Network) and RFE (recursive feature elimination)	IEEE	Accuracy and Loss	NA
#8	Not Linked to GitHub	Not Linked to GitHub	Data from: High-throughput adaptive sampling for whole-slide histopathology image analysis (HASHI) via convolutional neural networks: application to invasive breast cancer detection	Whole Slide Images & HASHI & CNN's & Adaptive gradient-based sampling algorithm	Zenodo	AUC, Dice, PPV, NPV, TPR, TNR, FPR, and false negative rate (FNR).	NA
#9	Breast Cancer Classification Paper	convolutional neural network (CNN) models could outperform standard CNNs when trained on Digital Breast Tomosynethesis (DBT) images	Breast_Cancer_Classification_Paper.pdf - Within GitHub	NA	GitHub	AUC and Accuracy	No - From Separate Sources
#10	Not Linked to GitHub	Not Linked to GitHub	Breast cancer diagnosis from mammographic images using optimized feature selection and neural network architecture	Breast cancer detection model - five major phases: preprocessing, segmentation, feature extraction, feature selection, and classification.	Web of Science	accuracy, specificity, Precision, FPR, FNR, NPV, FDR, F1-score, and MCC	NA

In the literature review, the main topics for this ranking were shared in detail. One of the main domain discussed were related to computer-aided detection (CAD) systems that was used for classifying benign and malignant breast tumors in mammography images. Instead of using a potentially harmful contrast agent in MRI, these CAD systems help differentiate tumor types in mammography samples. The method employs deep learning with SVM. The CAD system involves five main steps: image enhancement, segmentation, extracting features, classifying features, and evaluating the classifier (Ragab et al., 2019).

Moreover, the literature review also discussed another domain using neural network models combined with MIAS and CBIS-DDSM datasets for Tumor classification in mammograms. This method uses histological images for precise benign and malignant tumor identification, (Kumar et al., 2022).

Lastly, using deep convolutional neural networks has also shown high accuracy in diagnosing breast cancer and was discussed as one of the main domains in the literature review. In this method, neural networks and machine learning were used to categorize different types of breast cancer. And the method combines RFE, CNN, ANN, and DNN for feature selection (Asha et al., 2023).

Overall, the literature review that was completed helped me understand that, the manual extraction of features from medical images is a requirement for traditional ways of classifying breast cancer images, and these approaches can be harmful to patients by triggering allergic reactions, for example. The combination of machine learning, image classification, pattern recognition, etc. allows for the use of artificial intelligence in a wide range of contexts. Convolutional neural networks, whole slide histopathy image analysis, computer-aided diagnosis (CAD), the Mammographic Image Analysis Society (MIAS), and other techniques are examples of this. And in the second part of the research project, such pattern recognition and AI methodologies were further explored.

Part 2 – Code Set Assessments

The second part of the project involved assembling two primary datasets—one for breast cancer detection and the other for COVID-19 detection. It also encompassed a thorough exploration of Convolutional Neural Networks (CNNs), delving into their architecture and functionality to highlight their crucial role in identifying anomalies. The core research challenge in this phase revolved around the intricate correlation between computer science and health informatics, employing AI techniques to recognize patterns for cancer detection.

Taking a multidisciplinary approach, the study reviewed and implemented existing CNNs, focusing on their efficacy in pattern recognition for identifying anomalies. To evaluate the CNNs' pattern recognition performance, I compared two specific structures—MASK R-CNN and AlexNet (as introduced earlier in the introduction)—using various DICOM images representing different image types, including chest x-rays and breast mammograms. The chosen code sets were sourced from publicly available repositories on GitHub.

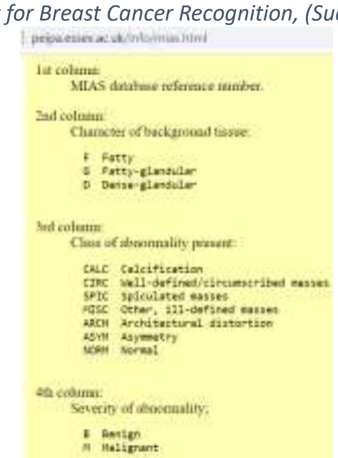
Data Availability and Image Sizing

The DICOM images and Python code used in the study were sources from publicly available repositories on GitHub as mentioned earlier. These data sources had distinct structures. For tumor detection, the images had predetermined sizes ranging from 100x100 to 1024x1024, (Kelly et al., 2021). On the other hand, for COVID detection, the images were resized to 244x244 pixels as required by the code's structure, (Zhao, 2020).

Breast Cancer Detection

Using the Mask R-CNN neural network, we analyzed a dataset for breast cancer recognition in mammogram images (Figure 8). Mask R-CNN is an extension of Faster R-CNN specifically designed for tumor detection. The code's classifications successfully located tumors and identified their types. We employed CNN layers with 1 to 4 hidden convolution layers, containing 10 to 128 filters, and 1 to 5 dense layers with 120 to 2000 nodes for this implementation, (Kelly et al., 2021).

Figure 8:Dataset for Breast Cancer Recognition, (Suckling et al., 1994)



1st column:
MIAS database reference number.

2nd column:
Character of background tissue:

F Fatty
G Fatty-glandular
D Dense-glandular

3rd column:
Class of abnormality present:

CALC Calcification
CIRC Well-defined/circumscribed masses
SPIC Spiculated masses
MISC Other, ill-defined masses
ARCH Architectural distortion
ASYM Asymmetry
NORM Normal

4th column:
Severity of abnormality;

B Benign
M Malignant

The method of CNN's called Mask R-CNN extends the Faster R-CNN as mentioned earlier on in the paper. But in this extension, we add a branch for prediction segmentation masks on the region of interest also known as ROI, (He et al., 2017). This is added in parallel with the existing branches for the classification and bounding box regression. Please reflect to Figure 9 and 10, to see clearly how this framework is organized. Mask R-CNN is an advanced version of Faster R-CNN, which is a model that has the ability to detect and locate objects in images, (He et al., 2017).

While Faster R-CNN tells us what objects are in the image and where they are located with bounding boxes, Mask R-CNN goes one step further and adds a third output, which is the exact shape of each object, like a precise outline or mask, (He et al., 2017). The Mask R-CNN is simple to implement, and train given the Faster R-CNN framework. Additionally, Mask R-CNN is conceptually simple to understand. To give an easier example, image we were to feed the model images of breast mammographs with tumors present. In this case the Faster R-CNN can tell you there is tumor present on the mammographs. But Mask R-CNN can also draw the outline of where the tumor exists in each of the mammographs. Which is why Mask R-CNN is so useful in health care. To see an example of how Mask R-CNN creates these boundaries on images, please refer to Figure 10. However, this process of creating these outlines is more challenging because it requires very detailed information about the anomaly's boundaries, (He et al., 2017). Mask R-CNN uses a technique called "pixel-to-pixel alignment" to figure out these exact shapes accurately.

Figure 9: Mask R-CNN Framework, (He et al., 2017)

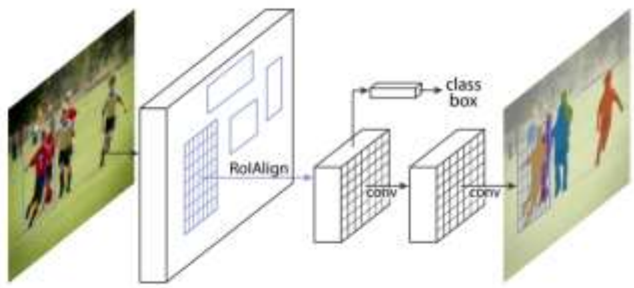


Figure 10: Mask R-CNN Framework, (He et al., 2017)

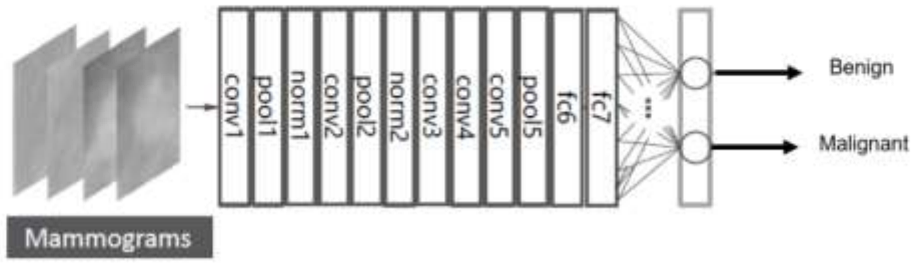
Covid-19 Detection

For the detection of Covid-19, the dataset utilized AlexNet. This python code source from GitHub was used to develop a prototype in this project that categorises and determines whether chest x-rays for covid-19 are positive or negative. To prevent computational complexity, the number of layers and parameters is decreased. Two convolutional layers, two max-pooling layers, one hidden layer, and one output layer makes up this structure. Batch normalisation is used to normalise the produced data in between layers.

AlexNet, which is used in this part of the project, is often referred to as the "pioneer" of CNNs, holds the distinction of being optimized for classifying a thousand different classes, (Zhao, 2020). However, it also demands a tremendous amount of memory and computational power during training due to the large number of mathematical operations involved, (Zhao, 2020). This deep learning architecture called

AlexNet has made substantial advancements in computer vision. As mentioned earlier in the paper, AlexNet is a convolutional neural network (CNN) consisting of five convolutional layers, followed by three fully connected layers, (Zhao, 2020). In this project, AlexNet is employed to determine whether chest images fed into the model contain COVID-19 or not. However, if we were to utilize AlexNet for identifying benign or malignant breast cancer, the model's structure would resemble the one depicted in Figure 11.

Figure 11: AlexNet for Breast Cancer Detection, (Ragab et al., 2019)



Results

In this section, I will present the outcomes obtained upon executing both sets of code.

Breast Cancer Detection

In this code set, 322 mammograms from the Mammographic Image Analysis Society, or MIAS, were used from a total of 161 patients. Every image utilised from this dataset is 1024 by 1024 pixels and has a 200 micron pixel edge reduction. There were a few factors in this dataset that were crucial to take into account. The characteristics of the background tissue, for instance, were divided into three categories: Fatty, Fatty-glandular, and Dense-glandular. In addition, a wide range of types of abnormalities, including calcification, well-defined/circumscribed masses, spiculated masses, poorly defined masses, architectural distortion, asymmetry, and normal, were taken into account. Finally, it's critical to classify these photos according to the severity of the anomaly, depending on whether the mass is benign or malignant. The specified categories hold significant importance in both bioinformatics and health informatics due to their role in accurate tumor classification and subsequent clinical decision-making.

Part A - Dataset Cleaning

There are three primary sections to this code set. We will concentrate on Part A in this section, which deals with dataset cleaning. Here, we read image files and pull-out essential information. Our main goal is to locate tumour-containing photos and eliminate duplicates to ensure a clean dataset. Creation of visuals is possible to help us understand the data when the cleaning procedure is finished, and duplicates have been eliminated. The graph, which is displayed in Figure 12, demonstrates the proportion of photos with and without tumours.

Figure 12: Proportion of Mammograms with and without Tumour

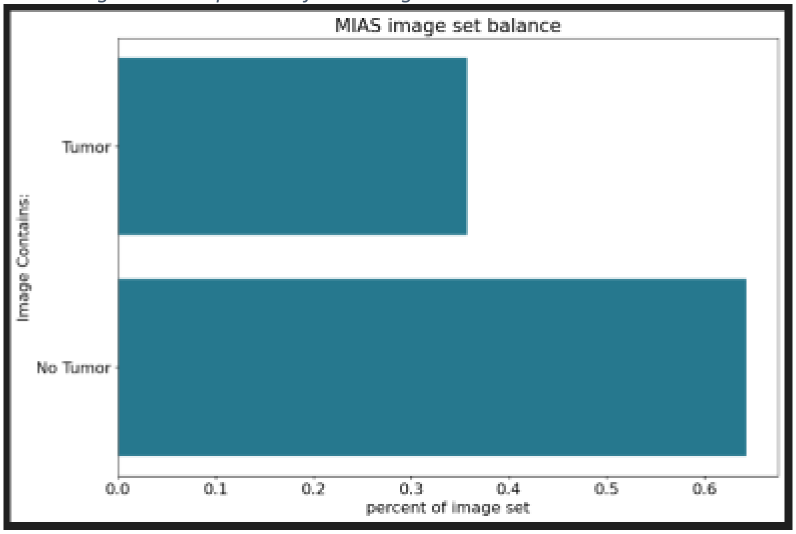


Figure 12 elegantly illustrates the identification process of mammograms, determining the presence of tumors based entirely on the categories detailed earlier in this document. These categories encompass background tissue, abnormality type, and the anomaly's severity.

Furthermore, our capabilities extend to creating informative graphs that present data about different abnormality types, accompanied by references to background tissue. For a deeper understanding, please see Figures 13 and 14.

Figure 13: Distinct abnormalities

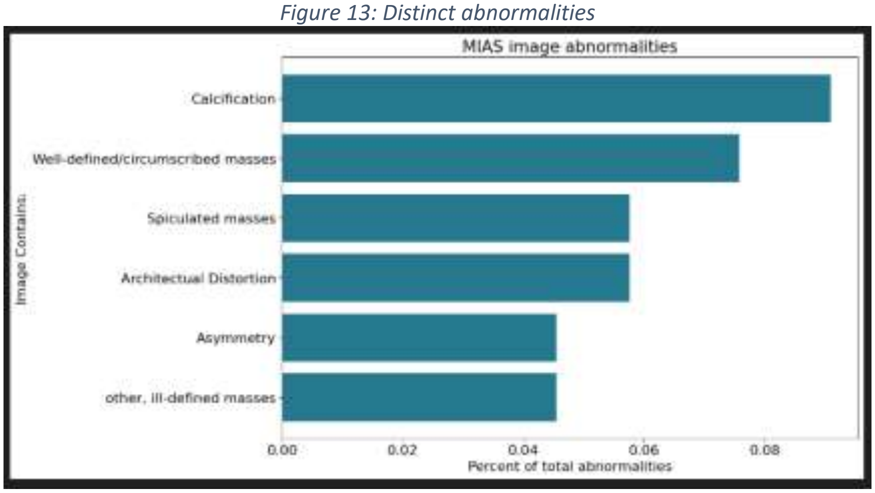
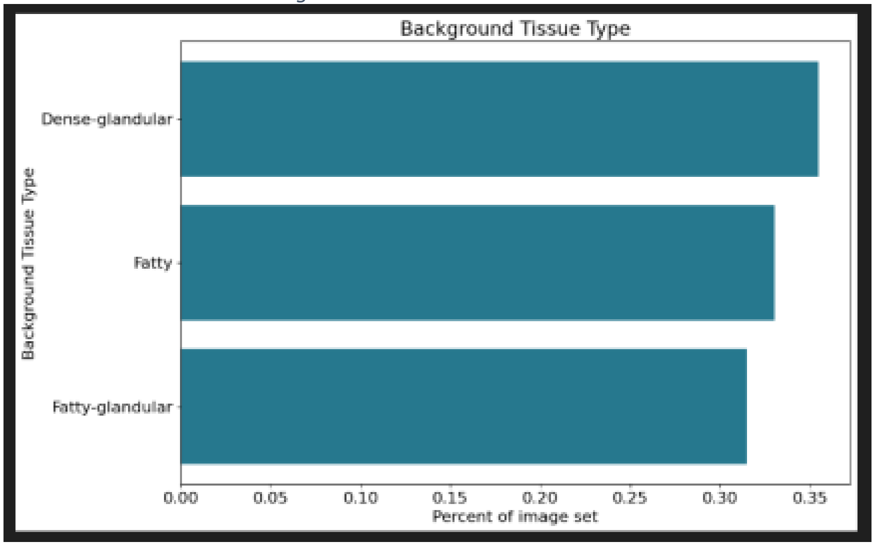
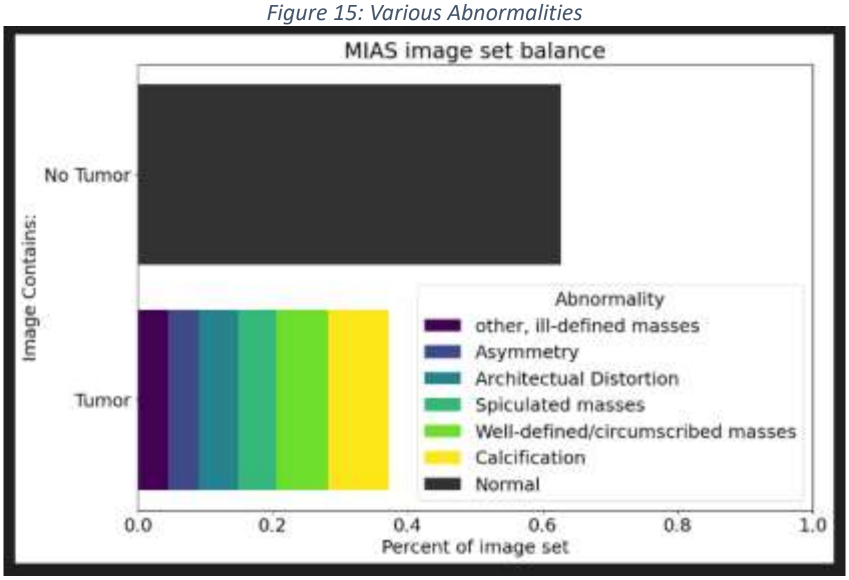


Figure 14: Distinct abnormalities



To enhance data comprehension and enable a focused comparison between tumor and non-tumor cases, as well as various abnormalities, we generated specific visuals (see Figure 15).

Figure 15: Various Abnormalities



The abnormalities shown in the Figure 13, describe different types of anomalies that can be present in medical imaging, particularly in the context of tumor classification. These classifications are crucial in bioinformatics and health informatics because these different categories can help identify the severity of the mass found on the breast tissue.

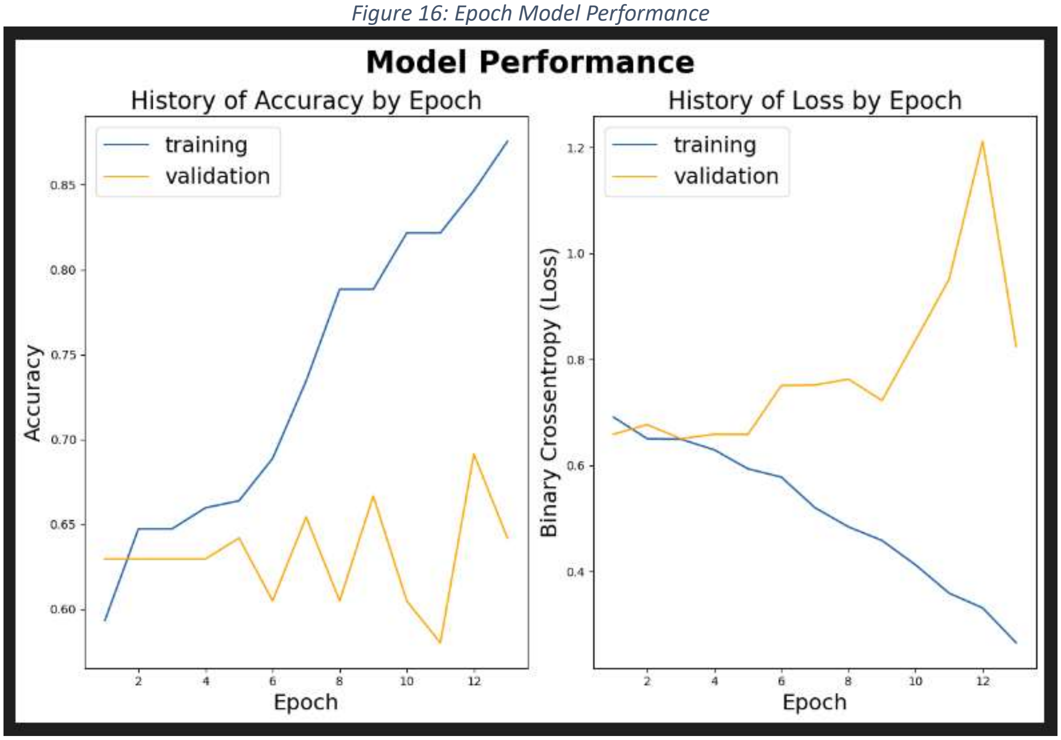
Additionally, in Figures 14 and 13, we can observe how well the model detects tumors in mammograms, considering different breast density variations like Fatty, Fatty-glandular, and Dense-glandular. Studies highlight that breast density affects how well algorithms find breast cancer (Wang et al., 2018). Typically, lumps in low-density images have distinct visual traits that help with accurate detection (Wang et al., 2018). However, in areas with high density, errors in the final recognition step can lead to more false alarms (Wang et al., 2018).

Breast density also relates to the anomaly categories shown in Figure 14. These categories include calcification, well-defined/circumscribed masses, spiculated masses, poorly defined masses, architectural distortion, asymmetry, and normal appearances. This connection matters because an algorithm's effectiveness can be influenced by both breast density and the specific type of anomaly it's trying to find. This influence impacts how well it detects breast cancer accurately (Wang et al., 2018).

Part B – Model Training

Moving on to part B, the training procedure is carried out using the "cnn.fit" approach in this section. We randomly divide the data using a random seed, and we can then determine how many epochs are required for this model to produce reliable findings. In the context of machine learning, epochs refer to the number of times a model examines and absorbs information from the entire training dataset, (Zhao, 2020). In other words, an epoch is a single time when the model iterates over the dataset. Figure 16 displays the model's performance accuracy as well as the loss in terms of the epochs' historical development.

Figure 16: Epoch Model Performance



I would like to discuss how epochs work in this model and what they mean. Think of epochs as training cycles for the model. As we examine the code, we notice that during training, the model keeps an eye on validation and loss. Based on these, it decides whether to keep training or stop. Let's break down "validation" and "loss." Imagine there are values set in the code that decide how much improvement should happen for training to continue. If the monitored value doesn't show improvement, it means the model isn't getting better, so it's at a "loss." On the other hand, if the value shows improvement, there's no loss – the model is getting better.

Figure 16 helps us understand this better. On the graph, accuracy (how well the model detects breast cancer) and loss (epochs that don't improve the model) are shown. Accuracy goes up with each training round, each epoch. But if the graph for loss goes up, it means the extra epochs aren't helping accuracy anymore. This happened at the end of the second graph – the model already learned a lot, so more epochs didn't add to its accuracy. In a way, the model had reached its training limit. So, epochs are like rounds of practice for the model. It checks if things are getting better or not. This understanding helps us decide when to stop training – when extra rounds won't make the model better anymore. Following is a table that shows how long it took to run all the fifteen epochs.

Table 1: Epochs Iteration Time Stamps

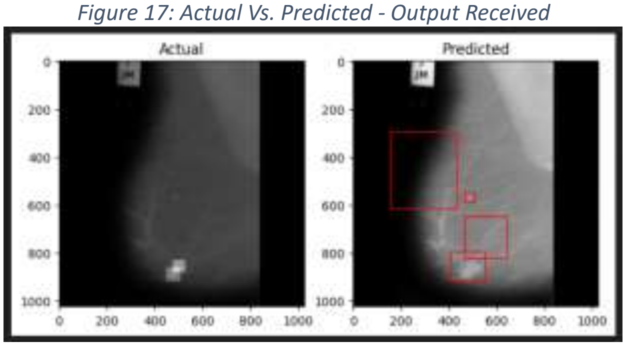
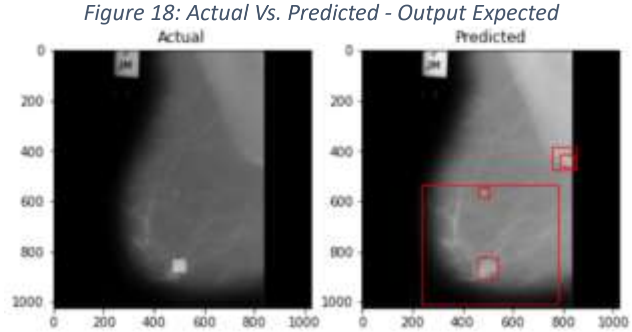
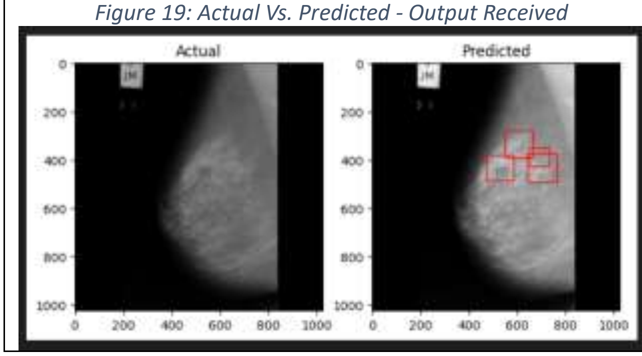
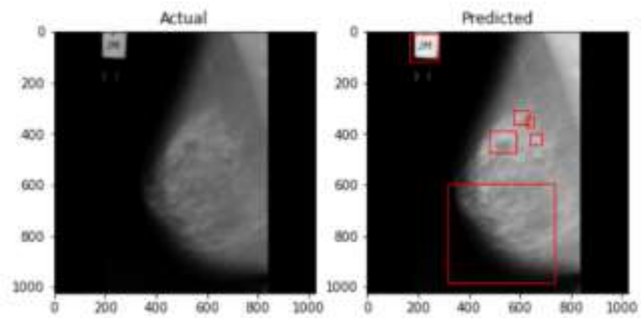
Epoch / Iteration Number	Approximate Time Iteration Required	Approximate Time Iteration Ended
1	2 Hours 48 Minutes	5:50 PM
2	2 Hours 48 Minutes	8:31 PM
3	2 Hours 48 Minutes	11:23 PM
4	2 Hours 48 Minutes	1:40 AM
5	2 Hours 48 Minutes	3:20 AM
6	2 Hours 48 Minutes	5:30 AM
7	2 Hours 48 Minutes	7:40 AM
8	2 Hours 48 Minutes	9:55 AM
9	2 Hours 48 Minutes	12:10 PM
10	2 Hours 48 Minutes	2:55 PM
11	2 Hours 48 Minutes	5:25 PM
12	2 Hours 48 Minutes	7:43 PM
13	2 Hours 48 Minutes	9:58 PM
14	2 Hours 48 Minutes	12:30 AM
15	2 Hours 48 Minutes	3:20 AM

Furthermore, the reasoning for our decision to choose the ninth H5 file above alternatives like file three is a critical one. The decision is based on the possibility that selecting file number three would result in mammography results with noticeably enlarged bounding boxes. These results would therefore not accurately represent the areas of interest as intended.

Part C – Model Execution

Moving on to part C, we do the mask fit and import the coco dataset, (Abdulla, 2019) from Mask R-CNN as a base in this step. In order to train the model, this phase executes the fifteen epochs. We are able to load this fit once the model has been trained and executed. The plots that are produced after the model has been trained show both the original breast photos and the output images with the ROI (region of interest) boxes. The ROI's are the bounding boxes that indicate the areas that have the chance of containing tumor. An illustration of one of the plots is shown in Figures 16 and 17 to compare to Figures 18 and 19.

Table 2: Comparing Outputs

Output – Model Training	Output – GitHub
Figure 17: Actual Vs. Predicted - Output Received 	*Figure 18: Actual Vs. Predicted - Output Expected* 
Figure 19: Actual Vs. Predicted - Output Received 	*Figure 20: Actual Vs. Predicted - Output Expected* 

Significant disparities exist among these outputs, stemming from several potential factors. A prominent contributor could be the inconsistent order in which breast mammograms are processed by the model, leading to variations in results. Additionally, differences might arise due to variations in model training methodologies, potentially influenced by how the data was divided using a random seed.

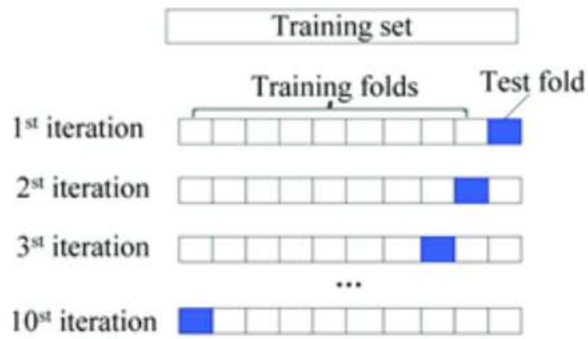
Covid-19 – Code Set

The data sets used to train and run this code base are from the University of Montreal (Cohen, 2020) and from Kaggle (Chest X-Ray Images, n.d.). This project only used 50 DICOM x-ray images for training and testing of the model.

Part 1 – Classifier Modelling

In this section of the code, we categorize data into pairs of images and labels, convert images to greyscale and reshape images to have a dimension recognizable by the CNN, (Zhao, 2020). In addition to this, in this section we also build the neural network. After that we are able to train and test the CNN with a 10-fold cross validation, (Zhao, 2020). Figure 21 reflects the visualization of these 10-fold cross validation process. This includes training the model with five iterations, these iterations are also known as epochs, (Zhao, 2020).

Figure 21: CNN with a 10-fold cross validation, (Zhao, 2020)



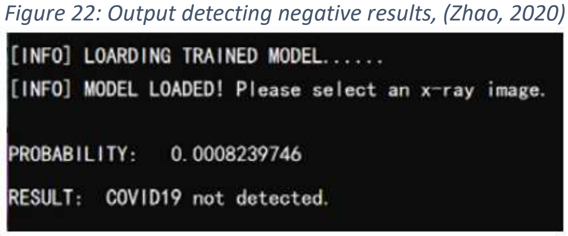
Part 2 – Classifier Evaluation

In this section we load the trained model and import and process the data.

Part 3 – Classifier Interface

In this section the user is able to select an image from their saved folders. This is done by using the Tk class which represents the main window of a Tk application. After the user selects the image, the model is used to predict the selected image and inform the output to the user. An example of the output is shown in Figure 22.

Figure 22: Output detecting negative results, (Zhao, 2020)



Discussion

Within this section, my intention is to explore the challenges I encountered during the course of this project, while also delving into the achievements and setbacks that marked its journey. Additionally, I will be discussing the major comparisons between both the neural networks and code sets. Furthermore, I'll outline the subsequent steps that warrant exploration for further investigation.

To understand the timeline of the project better, please refer to the Gantt chart, providing an insightful overview of the challenges encountered during the execution of both code sets. Additionally, it offers a detailed breakdown of the time dedicated to various aspects of assignment two. For more comprehensive information, please refer to Figure 23.

Figure 23: Challenges Encountered - Code Execution

Challenges

One of the major challenges that I ran into during this project was errors with the versioning of the python libraries to install for breast cancer installation. These errors included issues with the versions of TensorFlow, keras and Mask R-CNN. After running into all these errors, I took my time in researching online to find a solution and created the following notes.

Some of the key libraries utilized in Breast Cancer detection from Mammograms included:

- TensorFlow 1.15.0: A powerful deep learning library.
- Keras 2.3.1: A high-level API for building neural networks.
- Pandas 1.3.5: Employed for data manipulation and analysis in Python.
- Scikit-learn 1.0.2: A versatile machine learning library for tasks like classification and regression.
- Seaborn 0.12.2: Utilized for creating appealing data visualizations, built on top of Matplotlib version 3.5.3.
- NumPy 1.21.6: Utilised to handle big arrays and matrices in numerical computations.
- SciPy 1.7.3: Used for scientific computing and technical computing. In this case, it was utilized as it contains modules for image processing
- Pillow 9.5.0: Is an image library in python, used for opening, manipulating, and saving many different image file formats
- Cython 0.29.36: Primarily utilized to enhance the performance of Python code
- Scikit-image 0.19.3: Utilized in this situation as it offers a variety of image-processing capabilities and methods, including image filtering, segmentation, feature extraction, and picture transformations.
- OpenCV-Python 4.8.0.74: Used as it provides a wide range of functions and tools for working with images and videos
- H5Py 3.8.0: Used because it offers a user interface for interacting with the HDF5 (Hierarchical Data Format 5), which was the format for many of the data files used in this project.
- Imgaug 0.4.0: Python library used for image augmentation.

Comparison

The subsequent table provides a detailed breakdown of the distinctions between the two convolutional neural networks and offers a comparative analysis of the code sets, focusing on the anomalies they identify.

Table 3: Comparing Both Neural Networks

MRCNN – Breast Cancer Detection	AlexNet – Covid Detection
Number of Epochs Completed are fifteen	Number of Epochs Completed are five
Number of Epochs completed is based on how many will maximize the accuracy and minimize the loss	Number of Epochs were pre-determined
Mask R-CNN creates bounding boxes or a precise outline for the lesions. Therefore, requires detailed data and information on DICOM images.	Only detects if an anomaly is present or not without giving any outputs with bounding boxes or outlines for tumors
Number of convolutional layers depends the type of implementation	Have five convolution layers, three pooling layers, and two fully connected layers

In this section, I will delve into a more detailed analysis of the disparities highlighted in the preceding table. The visual results presented in the results section clearly indicate that running epochs in the breast cancer detection code set demanded significantly more time and complexity compared to the COVID-19 detection code set. This discrepancy holds implications and limitations that warrant closer examination. When training a model, “we expect the loss to decrease and accuracy to increase as the number of epochs increases”, (baeldung, 2023). Therefore, running a sufficient number of epochs is crucial for optimal model performance. While using Mask R-CNN for breast cancer detection, we were able to perform the necessary number of epochs to achieve the highest accuracy. Moreover, the visual representations from parts A and B of the code set confirmed the model's accuracy. However, in the case of the code set using AlexNet for COVID-19 detection, a limitation arose as there was no function to allow running epochs to their maximum for increased accuracy. Instead, the value of 5 was predetermined as the number of epoch iterations. This discrepancy in the number of epoch iterations could pose challenges when comparing the two code sets, as they had varying inputs in terms of how many epochs each model could run.

Furthermore, another difference is that Mask R-CNN can outline specific regions where differences occur, while AlexNet only determines if an anomaly is present or not. This highlights how distinct these two convolutional neural networks are, not only in their results but also in their architecture and requirements. For instance, creating these outlines in Mask R-CNN is more complex, as it needs detailed anomaly boundary information and uses "pixel-to-pixel alignment" for precise shape identification (He et al., 2017), which isn't necessary for AlexNet.

Further Investigation

In this section, I'll explore certain discrepancies that have surfaced during the project and offer insights into potential remedies for these issues, along with the need for further investigation. During the project review with Dr. William, several additional limitations came to light. Among them, one of the key concerns emphasized by Dr. William was the usage of only one angle for running the breast cancer mammograms. In a real-life hospital setting, radiologists and oncology specialists typically require multiple angles of the breast tissue to gain a comprehensive understanding of whether cancer is present or not. This limitation could potentially be a limitation in the implementation of this project in a real-world hospital scenario. However, this limitation could potentially be addressed as we expand our utilization of more DICOM images and data to thoroughly test the project code and its outcomes. This approach could pave the way for rectifying this issue and enhancing the project's real-world applicability.

Another notable limitation highlighted by Dr. William was that the testing was conducted solely using one dataset, specifically the MIAS dataset. To attain more robust and reliable results, running the model on different and multiple datasets would have been beneficial. The inclusion of diverse datasets would have provided clearer insights into the accuracy and effectiveness of the neural network model's outputs. I am aware that there are publicly available datasets, such as the Curated Breast Imaging Subset of Digital Database for Screening Mammography (CBIS-DDSM), which could have been utilized. However, due to the constraints of the project timeline, I regrettably could not proceed with running the model on this dataset. Nonetheless, it is critical to acknowledge that in future implementations of this project, exploring various datasets will be crucial to gain more of a comprehensive understanding of the model's performance and accuracy.

To gain a comprehensive understanding of the accuracy inherent in the developed models, a valuable approach involves interchanging the roles of both neural networks. This entails assessing the efficacy of AlexNet in detecting Breast Cancer and evaluating how effectively Mask R-CNN identifies Covid-19. Carrying out such a comparison in subsequent investigations could yield a deeper understanding of neural networks' accuracy across diverse anomaly detections. Additionally, it could shed light on which neural network proves more efficient and proficient within the domain of healthcare and health informatics.

Another avenue to explore in terms of further investigation involves extending the epochs and intensifying training while employing AlexNet for Covid-19 detection. As mentioned earlier in this paper, the code set for Covid-19 detection utilizes a predefined number of epochs, set at 5. However, it's intriguing to contemplate the outcome of employing a significantly larger number of epochs. Would this yield a more precise outcome? Such exploration would provide valuable insights into the role of epochs within the realm of pattern recognition methodologies.

Conclusion

Overall, in the context of computer science and health informatics, the utilization of DICOM Images, pattern recognition and AI has proven highly effective in image analysis and anomaly detection. These advancements are closely linked to improving patients' well-being, facilitating vital support from doctors throughout the diagnostic process. The integration of AI with medical imaging has the potential to revolutionize radiology workflows, leading to significant advancements in healthcare practices and benefiting patients on a considerable scale.

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