

**Detection of Breast Cancer using Deep Learning Approach**

**BY**

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This Report Presented in Partial Fulfillment of the Requirements for the  
Degree of Bachelor of Science in Computer Science and Engineering

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## APPROVAL

This Project/internship titled “**Detection of Breast Cancer using Deep Learning Approach**”, submitted by Badhan Saha, ID No: 181-15-2008 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *25 January 2023*.

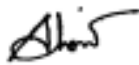
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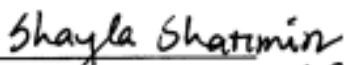
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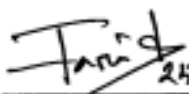
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## DECLARATION

I hereby declare that, this project has been done by me under the supervision of **Naznin Sultana, Associate Professor, Department of CSE** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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## **ABSTRACT**

Breast cancer is a disease in which cells in the breast grow out of control. In Bangladesh the rate of breast cancer occurrence is estimated to be 22.5 per 100,000 females of all ages. In case of Bangladeshi women, aged between 15-44 years, breast cancer has the highest prevalence 19.3 per 100,000 compared to any other type of cancer. Breast cancer can occur in both men and women, but it's far more common in women. There are many researches who have worked on detection of breast cancer using deep learning techniques. But their works are dedicated to one particular dataset. In this paper I try to detect the breast cancer by using a deep learning techniques Convolutional Neural Network (CNN). I also use three pre-trained CNN models VGG-16, Inception V3 & ResNet50 to compare with my CNN model. In this paper I worked with two datasets. One BreKHis dataset (Histopathology Image) & the another one (MRI Image) is taken from Kaggle. Aim of this paper is to detect the breast cancer by using deep learning model with maximum accuracy. The experimental results show that for histopathology image VGG-16 gives the highest accuracy of 99.32% and for the MRI image Inception V3 gives the highest accuracy of 95.36%. All experiments are executed within Jupyter Notebook, Google Colaboratory and PyCharm platform.

# TABLE OF CONTENTS

<b>CONTENTS</b>	<b>PAGE</b>
Board of examiners	ii
Declaration	iii
Acknowledgements	iv
Abstract	v
<b>CHAPTER</b>	
<b>CHAPTER 1: INTRODUCTION</b>	<b>1-2</b>
1.1 Introduction	1
1.2 Motivation	1
1.3 Objective	1-2
1.4 Expected Outcome	2
1.5 Report Layout	2
<b>CHAPTER 2: BACKGROUND STUDY</b>	<b>3-5</b>
2.1 Introduction	3
2.2 Literature Review	3-4
2.3 Research Summary	4
2.4 Tools and Software	5
2.5 Scope of the Problems	5
2.6 Challenges	5

<b>CHAPTER 3: RESEARCH METHODOLOGY</b>	<b>6-16</b>
3.1 Introduction	6
3.2 System Design	6
3.3 Data Collection Procedure	7
3.4 Data Pre-processing	7
3.5 Split the Data	8
3.6 Transfer Learning	8
3.7 Pre-trained Model	8-10
3.8 Training the Model	10
3.9 Model Configuration	11
3.10 Model Architecture	12-14
3.11 Parameter	15
3.12 Hyper Parameter Tuning	16
<b>CHAPTER 4: EXPERIMENTAL RESULTS AND DISCUSSION</b>	<b>17-25</b>
4.1 Introduction	17
4.2 Results / Output	17-25

<b>CHAPTER 5: IMPACT ON SOCIETY AND SUSTAINABILITY</b>	<b>26-27</b>
5.1 Impact on Society	26
5.2 Ethical Aspects	26
5.3 Sustainability Plan	27
<b>CHAPTER 6: CONCLUSION AND FUTURE SCOPE</b>	<b>28</b>
6.1 Conclusion	28
6.2 Recommendation for Future Study	28
<b>REFERENCES</b>	<b>29</b>
<b>APPENDIX</b>	<b>30-36</b>
<b>PLAGIARISM REPORT</b>	<b>37</b>



## LIST OF FIGURES

<b>FIGURES</b>	<b>PAGE NO</b>
Figure 3.2.1: System design	6
Figure 3.7.1: Architecture of VGG-16	9
Figure 3.7.2: Architecture of Inception V3	9
Figure 3.7.3: Architecture of ResNet50	10
Figure 3.10.1: Basic CNN architecture	12
Figure 3.10.2: CNN model architecture of histopathology images	13
Figure 3.10.3: CNN model architecture of MRI images	14
Figure 4.2.1: Training and validation accuracy & training and validation loss of CNN for histopathology image	18
Figure 4.2.2: Training and validation accuracy & training and validation loss of VGG-16 for histopathology image	18
Figure 4.2.3: Training and validation accuracy & training and validation loss of Inception V3 for histopathology image.	19
Figure 4.2.4: Training and validation accuracy & training and validation loss of ResNet50 for histopathology image.	19
Figure 4.2.5: Training and validation accuracy & training and validation loss of CNN for MRI image.	20
Figure 4.2.6: Training and validation accuracy & training and validation loss of VGG-16 for MRI image.	20
Figure 4.2.7: Training and validation accuracy & training and validation loss of Inception V3 for MRI image.	21
Figure 4.2.8: Training and validation accuracy & training and validation loss of ResNet50 for MRI image.	21
Figure 4.2.9: Confusion Matrix	22
Figure B1: Imported libraries	30
Figure B2: Pre-set parameters	30

Figure B3: Data splitting for histopathology images	31
Figure B4: Data splitting for MRI images	32
Figure B5: Image resizing and rescaling	32
Figure B6: CNN architecture of histopathology model	33
Figure B7: CNN architecture of MRI model	34
Figure B8: CNN model training for histopathology image	35
Figure B9: CNN model training for MRI image	36

## LIST OF TABLES

<b>TABLES</b>	<b>PAGE NO</b>
Table 3.3.1: Statistics of datasets	7
Table 3.11.1: Model parameters	15
Table 3.12.1: Hyper Parameters	16
Table 4.1.1: Model Accuracy	17
Table 4.2.1: Confusion matrix of CNN for histopathology images	23
Table 4.2.2: Confusion matrix of CNN for MRI images	23
Table 4.2.3: Classification report of CNN for histopathology images	24
Table 4.2.4: Classification report of CNN for MRI images	25

# CHAPTER 1

## Introduction

### 1.1 Introduction

One of the terrible diseases in this world is cancer and especially the breast cancer in women is very dangerous. The second major cause of women's death is breast cancer [1]. In 2017, around 252,710 new diagnoses of breast cancer were expected in women, and around 40,610 women almost died from the disease [2]. As per the World Health Organization (WHO) breast cancer will be diagnosed 19.3 million times by 2025 [3]. More than 13,000 women in Bangladesh are infected with breast cancer and over 7,000 die every year, according to data from the International Agency for Research on Cancer (IARC).

### 1.2 Motivation

In Bangladesh breast cancer remains the most dreadful cancer of women. It causes almost 69% death of women. This event rate rises daily as a result of public ignorance, lack of trust in medical care, incorrect screening, mistreatment, and lack of will to seek institutional care and management. So somehow if it happens that the breast cancer can be detected earlier then the patient might start the treatment earlier and may live. That is why I try to build a model based on deep learning which will detect the breast cancer depending on both histopathological and MRI images.

### 1.3 Objective

The objective of this paper is to detect the breast cancer by using deep learning technique. With the help of deep learning if we manage to detect the breast cancer earlier the patient may have chance to get proper treatment. To detect the cancer, I used Convolution Neural Network (CNN). In this paper, I try to focus on both histopathological & MRI images. To train the model I used two datasets. For histopathological image I used BreakHis dataset

[4] and the MRI image dataset was taken from Kaggle [5]. To detect the cancer, I used CNN which is very popular for the image classification.

## **1.4 Expected Outcome**

As I said earlier, my research will detect the breast cancer. And it will be lot easier for both doctors and patients to identify the cancer. So that they can take quick necessary action against it. My system will work upon two types of images like histopathology images & MRI images.

## **1.5 Report Layout**

In this chapter I try to cover some basic idea of “A deep learning model which will detect the breast cancer” and also describe about the motivation, objective and expected outcome for this research. In chapter two, focus on related literature review, research summary & tools and software which I used on this research. Chapter three is for research methodology. Chapter four is dedicated to experimental results. The impact of this research, on society and the sustainability is discus on chapter five. In the last chapter I keep the conclusion and the future scope of the work. In the last portion of the report I add, appendix and references.

## **CHAPTER 2**

### **Background Study**

#### **2.1 Introduction**

In this research I used CNN to build the model. I also used three pre-train CNN models which are VGG-16, Inception V3 & ResNet50 to compare with my model. I used Python as programming language and TensorFlow as deep learning library.

#### **2.2 Literature Review**

For the research I have reviewed some related papers. In [6] this paper the researchers used an ensemble voting ML technique for analysis breast cancer. Firstly, they had contrivance logistic algorithm on the datasets & implemented NN Contrivance logistic process. And they have seen that the suggested strategy has acquired the 98.50% precision. For this work, they took 16 features only into the consideration of breast cancer analysis.

For effective breast cancer detection, the researchers in this publication [7] suggested a hybrid model combining numerous Machine Learning (ML) methods, including Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), and Decision Tree (DT). These researchers' findings imply that the most often used technique for applications involving cancer diagnosis is SVM. In this paper, the SVM's maximum accuracy was 99.8%. and according to the researchers that can be improved to 100%.

In [8] this paper the researchers compare the performance between different machine learning algorithms, Support Vector Machine (SVM), Decision Tree (C4.5), Naive Bayes (NB) and k Nearest Neighbors (k-NN) on the datasets is conducted by Wisconsin Breast Cancer. Their experimental results show that SVM gives the highest accuracy (97.13%) with lowest error rate.

In [9] this paper the researchers developed an image analysis approach using deep learning to conduct image analysis on H&E stained breast tumor tissue. Image-based classifiers for tumor grade, ER status, PAM50 intrinsic subtype, histologic subtype, and risk of recurrence score were developed using a training set of 571 breast cancers (ROR-PT). Low-intermediate vs. high tumor grade (accuracy rate: 82%); ER status (accuracy rate: 84%); Basal-like vs. non-Basal-like (accuracy rate: 77%); Ductal vs. Lobular (accuracy rate: 94%); and high vs. low-medium ROR-PT score (accuracy rate: 75%).

In [10] this paper the researchers use AlexNet in the neural network to extract features from breast cancer images for training purposes. During the training and testing process, the proposed model achieves higher accuracy of 98.44% and 98.1%.

In [11] this paper the researchers use texture features for detection of cancer. These texture features are extracted from the ROI. The dataset is taken from DDSM Database which contains approximately 3000 cases and is being used worldwide for cancer research.

### **2.3 Research Summary**

In this research I used two datasets. One is for histopathology images which is BreacKHis dataset. And the another one is for MRI images which is taken from Kaggle. For image classification I used CNN & also three pre-trained models which are VGG16, Inception V3 & ResNet50. For my CNN model I have divided both datasets into three-part 80% training, 10% validation & 10% testing. And for the pre-trained models I divided both datasets into two part 80% is for training and the rest 20% is for validation. I keep the image size 224 X 224 and other augmentation properties. After the training I have achieved maximum 99.32% of accuracy for histopathology image in VGG-16 and for the MRI image I have got 95.36 % accuracy in Inception V3.

## **2.4 Tools and Software**

For this research I have use Python as programming language. To use deep learning and high-level neural network I install Keras and TensorFlow in both Anaconda Navigation and Google Colaboratory. I also used PyCharm to create API in backend.

## **2.5 Scope of the Problem**

There are so many ways to identify the breast cancer. But my research is dedicated to only two type of images which are histopathology & MRI images. So, others image could not be identified by this model.

## **2.6 Challenges**

Collecting the datasets wasn't very hard part. The challenging part was to train the models and doing epochs because of having no external GPU in my system. So, it takes a lot of times to train my models.



# CHAPTER 3

## Research Methodology

### 3.1 Introduction

This chapter is all about dataset, data pre-processing, data augmentation, data split and transfer the train data into TensorFlow for training the model. In every step after the training, it takes a look at validation data and send data for testing. And finally, the data is sent for testing. All those steps will be discussed in this chapter.

### 3.2 System Design

The system design is shown in figure 3.2.1:

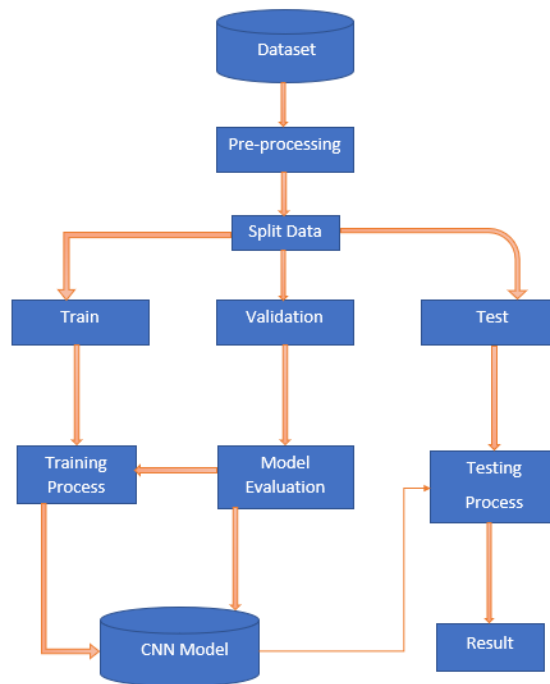


Figure 3.2.1: System design

### 3.3 Data Collection Procedure

In my work I used two types of datasets. One is histopathology image dataset & another is MRI image dataset.

I have used BreaKHis dataset for histopathology image. The dataset is publicly available. The dataset contains 7909 breast cancer histopathology images acquired on 82 patients. In which 2480 images are benign and 5429 images are malignant.

And the MRI dataset is taken from Kaggle. There are 600 female patients in all. There are 780 photos in the dataset. In which 437 images are benign, 210 are malignant and 133 are normal images. In this table 3.3.1 I shown the detailed statistics of both datasets.

Table 3.3.1: Statistics of datasets

Label	Total no of images	No of benign images	No of malignant images	No of normal images	Image format	Image size
Histopathology Image	7909	2480	5429	0	PNG	700*460
MRI Image	780	437	210	133	PNG	500*500

### 3.4 Data Pre-processing

In this pre-processing stage I resize the images into 224\*224 pixels and normalized the RGB values into -1 to 0 and 1 by rescale = 1.0/255.

### 3.5 Split the Data

The histopathology dataset has two categories benign and malignant, on the other hand the MRI dataset has three categories benign, malignant and normal. I have divided both the datasets into 80% training, 10% validation and 10% for testing for my CNN model. And I also split both datasets into two part 80% training & 20% validation for three pre-trained models.

### 3.6 Transfer Learning

Transfer learning is a method for transferring knowledge from one model to another in deep learning and machine learning. This process is basically used when the amount of data is small to properly train the model. In this case I have use the VGG-16, Inception V3 & ResNet50 to compare with CNN model. And to see that which model perform better.

### 3.7 Pre-trained Model

To comparison my CNN model I have used three pre-trained CNN models. They are,

#### **VGG-16:**

The network receives a dimensioned image as input (224, 224, 3). The same padding and 64 channels with a 3\*3 filter size are present in the first two layers. Then, two layers have convolution layers of 128 filter size and filter size following a max pool layer of stride (2, 2) (3, 3). The next layer is a max-pooling stride (2, 2) layer that is identical to the layer before it. There are then 256 filters spread across 2 convolution layers with filter sizes of 3 and 3. There are then two sets of three convolution layers, followed by a max pool layer. Each filter has the same padding and has 512 filters of size (3, 3). The stack of two convolution layers is then given this image. Finally, 3 dense layers are using to calculate the output. In this figure 3.7.1 I have shown the architecture of VGG-16.

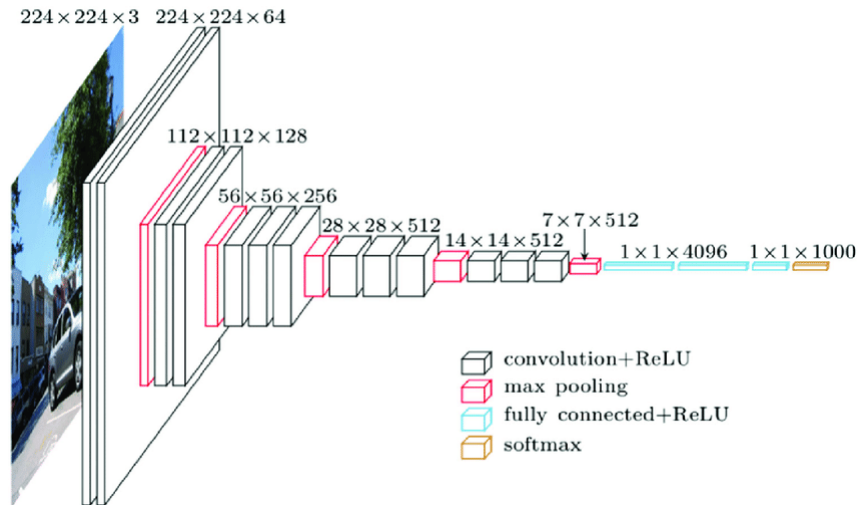


Figure 3.7.1: Architecture of VGG-16

### Inception V3:

Convolutional neural network model Inception-v3 has 48 layers and was pre-trained. It is a network that has been trained using a variant of the ImageNet database's more than a million photos. In this figure 3.7.2 I have shown the architecture of Inception V3.

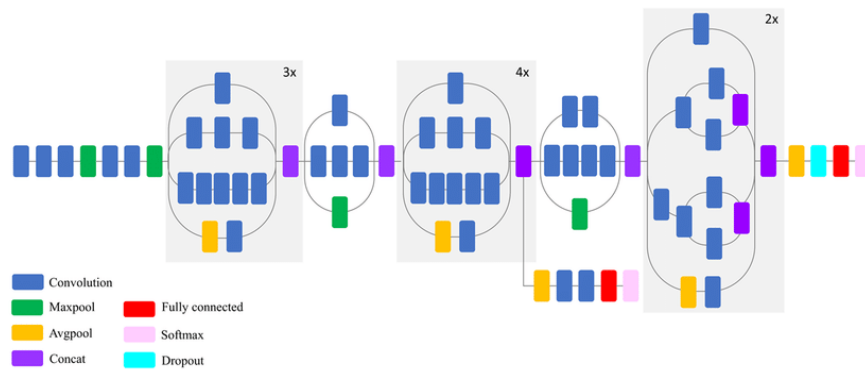


Figure 3.7.2: Architecture of Inception V3

## ResNet50:

There are 5 stages in the ResNet-50 model, each with a convolution and an identity block. Each identity block and each convolution block each have three convolution layers. There are around 23 million trainable parameters in the ResNet-50. In this figure 3.7.3 I have shown the architecture of ResNet50.

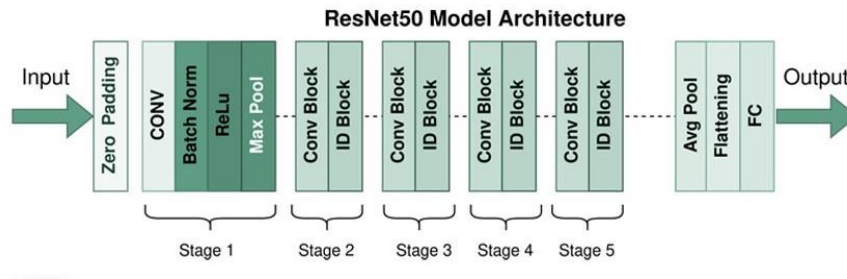


Figure 3.7.3: Architecture of ResNet50

## 3.8 Training the Model

To train the model I used CNN. I also used three pre trained CNN models VGG-16, Inception V3 & ResNet50 to compare with my model. I chose Jupyter Notebook and Google Colaboratory for the programming. To train the model I need to determine the batch size and epochs that will be discussed below:

### Batch Size

The amount of training samples used in one iteration is referred to as the "batch size" in deep learning. In this study, I define the batch size as 32.

### Epoch

A hyperparameter known as "epochs" determines how many times the learning algorithm will run through the full training dataset. In this study I keep the number of epochs 20 for all the models.

### **3.9 Model Configuration**

Convolutional Neural Networks, also known as CNNs, are a subset of artificial neural networks used in deep learning and are frequently employed for object and picture recognition and categorization. Thus, Deep Learning uses a CNN to identify items in a picture.

#### **Convolutional Layers**

The foundation of a CNN is a convolutional layer. It has a number of filters or kernels whose parameters must be learned over the course of training. Typically, the filters' size is smaller than the original image. Each filter produces an activation map after it convolves with the image.

#### **Max Pooling**

A pooling procedure called max pooling determines the highest or greatest value in each patch of each feature map. By offering an abstracted version of the representation, max pooling aids in reducing over-fitting. Additionally, it gives the internal representation fundamental translation invariance and lowers the computational cost by lowering the number of parameters to learn.

#### **Fully Connected Layer**

Fully Connected layers in neural networks are those layers where all the inputs from one layer are connected to every activation unit of the next layer. It also known as linear layers, connect every input neuron to every output neuron and are commonly used in neural networks.

### 3.10 Model architecture

Tensor Flow is a powerful tool that makes it easy to create, train, and deploy Machine Learning or Deep Learning models. I create CNN model for both type datasets to process the images. A deep neural network class called a convolutional neural network is frequently used to analyze visual imagery. A simple architecture of CNN is given bellow in figure 3.10.1

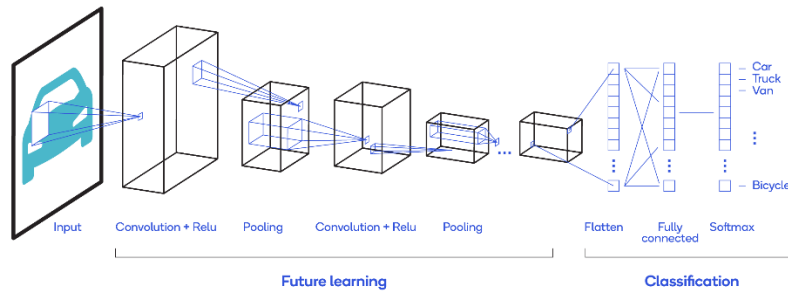


Figure 3.10.1: Basic CNN architecture

### Architectures

The architecture of my CNN models for both datasets are given bellow. In figure 3.10.2 and 3.10.3 I have given my two CNN models architecture for histopathology and MRI images.

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 224, 224, 3)	0
conv2d (Conv2D)	(32, 222, 222, 32)	896
max_pooling2d (MaxPooling2D)	(32, 111, 111, 32)	0
conv2d_1 (Conv2D)	(32, 109, 109, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(32, 54, 54, 64)	0
conv2d_2 (Conv2D)	(32, 52, 52, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(32, 26, 26, 64)	0
conv2d_3 (Conv2D)	(32, 24, 24, 64)	36928
max_pooling2d_3 (MaxPooling2D)	(32, 12, 12, 64)	0
conv2d_4 (Conv2D)	(32, 10, 10, 64)	36928
max_pooling2d_4 (MaxPooling2D)	(32, 5, 5, 64)	0
conv2d_5 (Conv2D)	(32, 3, 3, 64)	36928
max_pooling2d_5 (MaxPooling2D)	(32, 1, 1, 64)	0
flatten (Flatten)	(32, 64)	0
dense (Dense)	(32, 64)	4160
dense_1 (Dense)	(32, 2)	130

=====  
Total params: 171,394  
Trainable params: 171,394  
Non-trainable params: 0  
=====

Figure 3.10.2: CNN model architecture of histopathology images



```

Model: "sequential_1"

```

Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 224, 224, 3)	0
conv2d (Conv2D)	(32, 222, 222, 32)	896
max_pooling2d (MaxPooling2D)	(32, 111, 111, 32)	0
conv2d_1 (Conv2D)	(32, 109, 109, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(32, 54, 54, 64)	0
conv2d_2 (Conv2D)	(32, 52, 52, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(32, 26, 26, 64)	0
conv2d_3 (Conv2D)	(32, 24, 24, 64)	36928
max_pooling2d_3 (MaxPooling2D)	(32, 12, 12, 64)	0
conv2d_4 (Conv2D)	(32, 10, 10, 64)	36928
max_pooling2d_4 (MaxPooling2D)	(32, 5, 5, 64)	0
conv2d_5 (Conv2D)	(32, 3, 3, 64)	36928
max_pooling2d_5 (MaxPooling2D)	(32, 1, 1, 64)	0
flatten (Flatten)	(32, 64)	0
dense (Dense)	(32, 64)	4160
dense_1 (Dense)	(32, 3)	195

```

=====
Total params: 171,459
Trainable params: 171,459
Non-trainable params: 0

```

Figure 3.10.3: CNN model architecture of MRI images

### 3.11 Parameter

Parameters are learned or estimated purely from the data during training as the algorithm used tries to learn the mapping between the input features and the labels or targets. All the trainable and non-trainable parameters for my CNN and three pre-trained models VGG-16, Inception V3 & ResNet50 are given in table 3.11.1

Table 3.11.1: Model parameters

<b>Image Type</b>	<b>Model</b>	<b>Total Parameter</b>	<b>Trainable Parameter</b>	<b>Non-trainable Parameter</b>
Histopathology Image	CNN	171,394	171,394	0
	VGG-16	14,764,866	50,178	14,714,688
	Inception V3	21,905,186	12,402	21,802,784
	ResNet50	23,788,418	200,706	23,587,712
MRI Image	CNN	171,459	171,459	0
	VGG-16	14,789,955	75,267	14,714,688
	Inception V3	21,956,387	153,603	21802,784
	ResNet50	23,888,771	301,059	23587712

### 3.12 Hyper parameter tuning

Learning process is depended on hyper parameters. The performance of a model changes according to the response of hyper parameter. A list of hyper parameters which I have used in my model is given bellow in table 3.12.1:

Table 3.12.1: Hyper Parameters

No	Name of Hyper Parameter	Tuning
01	Epochs	20
02	Batch Size	32
03	Width, Height	224*224
04	Shuffle	True
05	Train, Validation & test	80%, 10%, 10%
06	Rescale	1.0 / 255
07	Horizontal & Vertical Flip	False
08	Model	Sequential
09	Activation	relu & softmax
10	Optimizer	adam
11	Loss	SparseCategoricalCrossentropy, binary_crossentropy
12	Metrics	Accuracy

## CHAPTER 4

### Experimental Results and Discussion

#### 4.1 Introduction

In this chapter I am going to discuss about the result. These results are taken from my final work. I have achieved a good accuracy from my models. In table 4.1.1 I have shown all the model accuracy.

Table 4.1.1: Model Accuracy

Image Type	Model	Accuracy
Histopathology Image	CNN	90.85%
	VGG-16	99.32%
	Inception V3	88.66%
	ResNet50	77.50%
MRI Image	CNN	94.35%
	VGG-16	91.04%
	Inception V3	95.36%
	ResNet50	70.24%

#### 4.2 Result/Output

##### Model Evaluation:

Without evaluation we cannot be able to understand how our model is working. In figure 4.2.1, 4.2.2, 4.2.3 & 4.2.4 I have given the training and validation accuracy & training and validation loss of CNN, VGG-16, Inception V3 & Resnet50 for histopathology images.

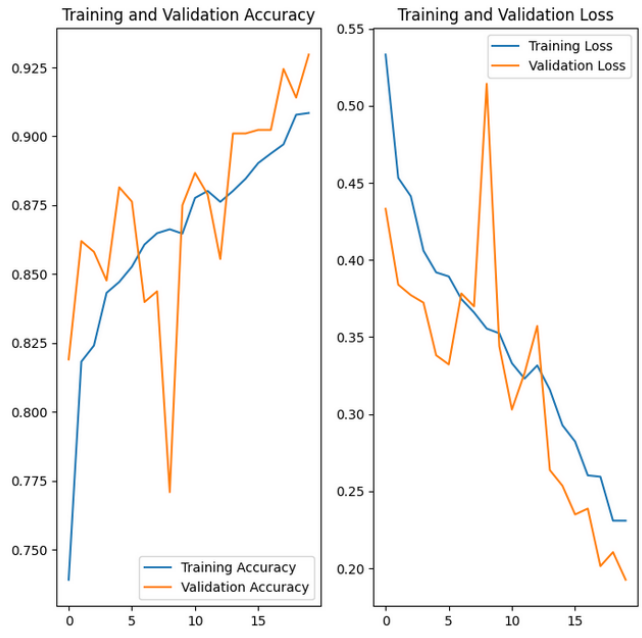


Figure 4.2.1: Training and validation accuracy & training and validation loss of CNN for histopathology image.

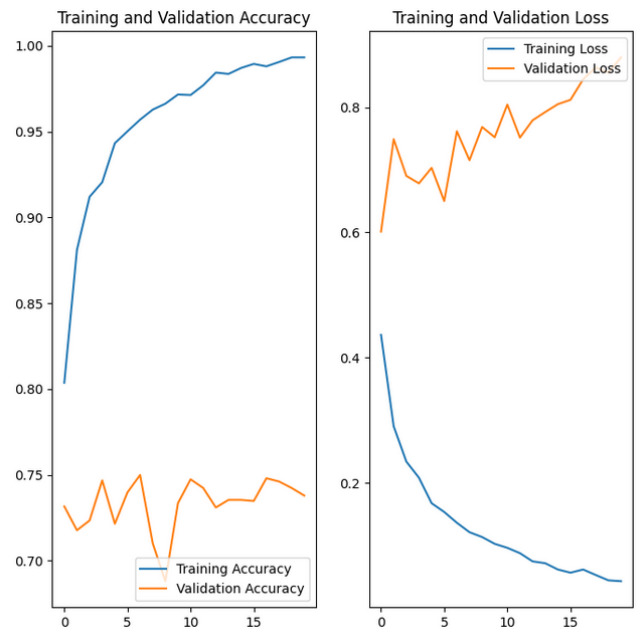


Figure 4.2.2: Training and validation accuracy & training and validation loss of VGG-16 for histopathology image.

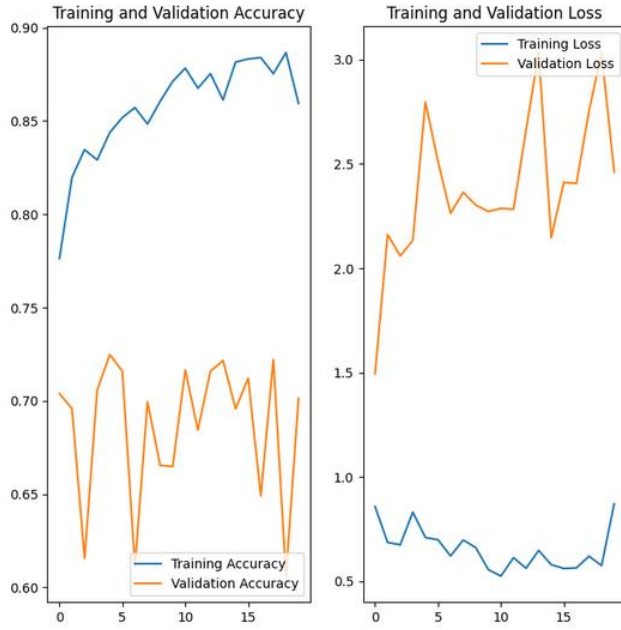


Figure 4.2.3: Training and validation accuracy & training and validation loss of Inception V3 for histopathology image.

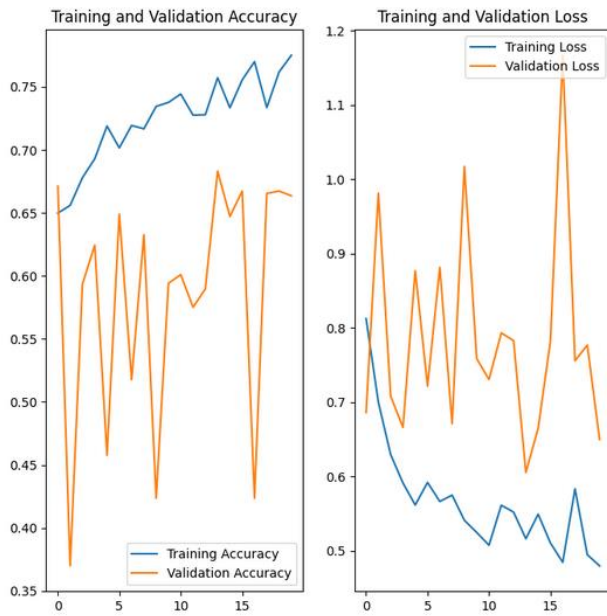


Figure 4.2.4: Training and validation accuracy & training and validation loss of ResNet50 for histopathology image.

In figure 4.2.5, 4.2.6, 4.2.7 & 4.2.8 I have given the training and validation accuracy & training and validation loss of CNN, VGG-16, Inception V3 & Resnet50 for MRI images.

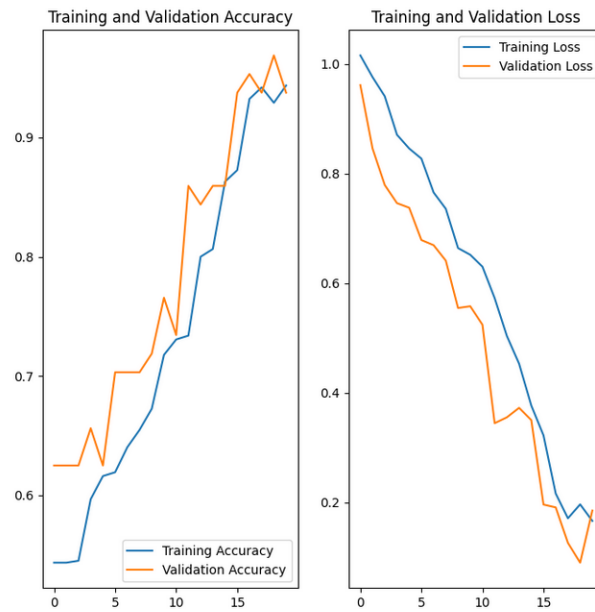


Fig 4.2.5: Training and validation accuracy & training and validation loss of CNN for MRI image.

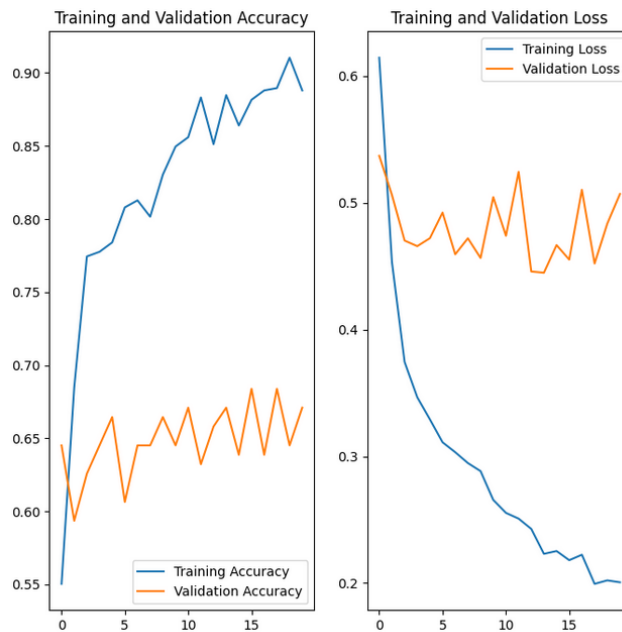


Fig 4.2.6: Training and validation accuracy & training and validation loss of VGG-16 for MRI image.

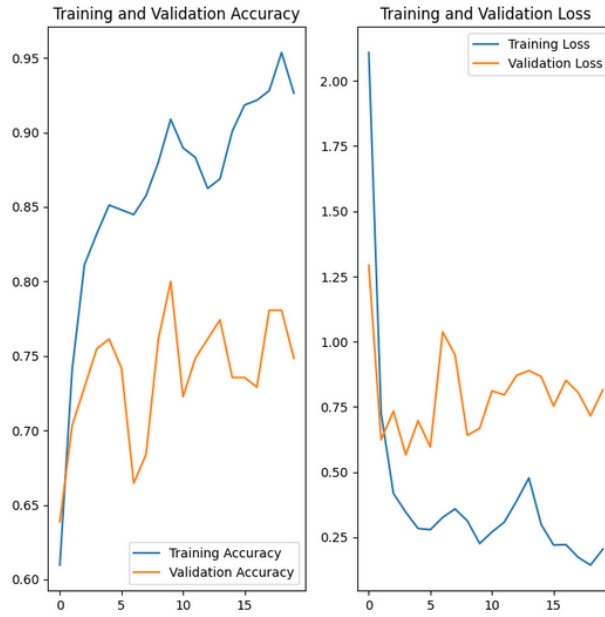


Fig 4.2.7: Training and validation accuracy & training and validation loss of Inception V3 for MRI image.

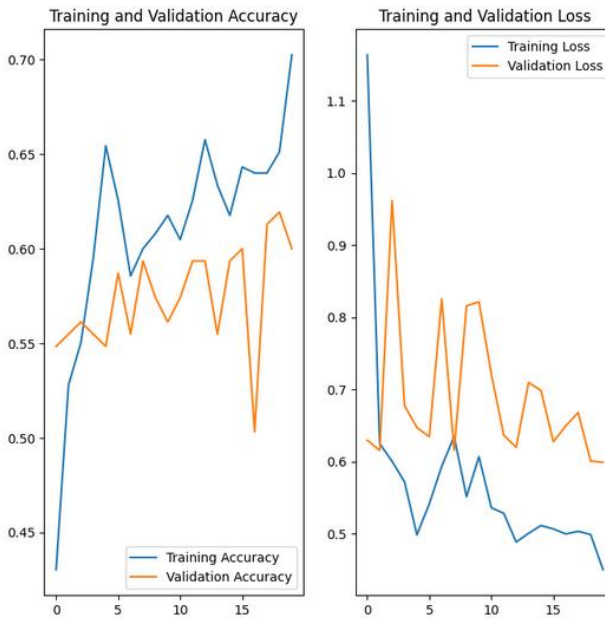


Fig 4.2.8: Training and validation accuracy & training and validation loss of ResNet50 for MRI image.



So, from the above figure we can say that, in the experiment may pre-trained model have more accuracy than my CNN model but CNN perform more stable than those three pre-trained models. For histopathology images VGG-16 achieved maximum accuracy of 99.32% but my CNN model performs better than other two pre-trained model InceptionV3 & ResNet50 and achieved accuracy of 90.85%. On the other hand, for MRI images InceptionV3 achieved maximum accuracy of 95.36% and my CNN model also achieved almost the same accuracy of 94.35% and performs better than other two pre-trained models VGG-16 & ResNet50.

**Confusion Matrix:**

A table called a confusion matrix is used to describe how well a classification system performs. A confusion matrix shows and sums up a classification algorithm's performance. Figure 4.2.9 represent the fundamental table of confusion matrix.

		True Class	
		Positive	Negative
Predicted Class	Positive	TP	FP
	Negative	FN	TN

Fig 4.2.9: Confusion Matrix

In table 4.2.1 & 4.2.2 I will show the confusion matrix for two CNN models.

Table 4.2.1: Confusion matrix of CNN for histopathology images.

<b>True Class</b> <b>Pred Class</b>	<b>Benign</b>	<b>Malignant</b>
<b>Benign</b>	360	157
<b>Malignant</b>	50	1020

Table 4.2.2: Confusion matrix of CNN for MRI images.

<b>True Class</b> <b>Pred Class</b>	<b>Benign</b>	<b>Malignant</b>	<b>Normal</b>
<b>Benign</b>	73	13	4
<b>Malignant</b>	9	25	4
<b>Normal</b>	4	3	21

### **Classification report:**

The accuracy of predictions made by a classification algorithm is evaluated using a classification report. how many forecasts come true and how many come truer. To be more precise, the metrics of a categorization report are predicted using True Positives, False Positives, True Negatives, and False Negatives. In table 4.2.3 & 4.2.4 I have shown the classification report of my two models. But before that, here is the sort description of precision, recall and f1-score

**Precision:**

Precision means out of all the positive classes we have predicted correctly, how many are actually positive.  $\text{Precision} = \text{True positive} / (\text{True Positive} + \text{False Positive})$

**Recall:**

It represents that out of all the positive classes, how much we predicted correctly. The higher values represent the better quality of model.  $\text{Recall} = \text{True positive} / (\text{True Positive} + \text{False Negative})$

**F1-score:**

F-score actually helps to measure Recall and Precision at the same time. It uses Harmonic Mean other than Arithmetic Mean.  $\text{F1-score} = (2 * \text{recall} * \text{precision}) / (\text{recall} + \text{precision})$

Table 4.2.3: Classification report of CNN for histopathology images.

<b>Dataset</b>	<b>Class</b>	<b>Precision</b>	<b>Recall</b>	<b>F1-score</b>
<b>Histopathology Image</b>	Benign	0.88	0.70	0.78
	Malignant	0.87	0.95	0.91
<b>Macro avg</b>		0.87	0.82	0.84
<b>Weighted avg</b>		0.87	0.87	0.87

Table 4.2.4: Classification report of CNN for MRI images.

<b>Dataset</b>	<b>Class</b>	<b>Precision</b>	<b>Recall</b>	<b>F1-score</b>
<b>MRI Image</b>	Benign	0.85	0.81	0.83
	Malignant	0.61	0.66	0.63
	Normal	0.72	0.75	0.74
<b>Macro avg</b>		0.73	0.74	0.73
<b>Weighted avg</b>		0.77	0.76	0.77

This chapter focused on the discussion of my experimental results. From the image of training and validation accuracy & training and validation loss and training and validation accuracy & training and validation loss, I can say that CNN was more stable than other three pre-trained models VGG-16, Inception V3, ResNet50. Also, in confusion matrix we can see the CNN model did a good number of right predictions. Although the model did some wrong predictions, but still, it is very less in numbers. The classification report gives the clear view of two CNN models for both histopathology and MRI images.

## **CHAPTER 5**

### **Impact on Social and Sustainability**

#### **5.1 Impact on Society**

Breast cancer is a condition in which the breast's cells proliferate out of control. Breast cancer diagnoses can have a profound emotional impact. Depression, anxiety, fear of the unknown, loneliness, and body image problems are a few of the typical mental health conditions. Nearly all cancer patients will experience psychological and emotional problems, which sometimes manifest years after therapy. Sometimes it depends on how earlier you can detect the cancer. If the cancer detected earlier the patient may take proper treatment and get well. As I have said before my model can detect the cancer from both histopathology and MIR images, I believe it will a good impact on society. With the help of this model, it will lot easier and correct for doctors to take the decision.

#### **5.2 Ethical Aspects**

According to a universal consensus and agreement, all diagnostic, curative and rehabilitative medical intervention and biomedical research on patients as human participants, including those related to breast disease and breast cancer, must be performed in a morally acceptable manner. In other words, a medical decision would be “right” if it is ethically justifiable. Similar to diagnosis and treatment of other diseases, people with breast problems such as breast cancer require medical and anthropological evaluations on one hand and ethical-legal analysis, on the other hand. As my model achieved higher accuracy, I can say that it will detect breast cancer well.

### **5.3 Sustainability Plan**

There have been significant improvements in cancer diagnosis and treatment during the last few decades. Equal access to the most recent scientific advancements and their cost, however, has become an issue due to the rising incidence of cancer and increasing strains on limited healthcare budgets. Past and current approaches to cancer care may not be sufficient for tomorrow. We face limited resources and a demand for cancer that will only increase in quantity and complexity in years to come. As a result, we need to find new ways to make the most of the resources we have. Improving the efficiency of cancer care must start with a clear understanding of what outcomes we are trying to achieve for patients. Each and every contribution means a lot like datasets, models etc. My project still in scratch. I'm trying to achieve more accuracy to do so need to monitor the datasets more precisely. I also need to do more experiment on those data such as augmentation, reshape etc. I also have a future plan to come with a developed software or a single page website.

## CHAPTER 6

### Conclusion and Future Scope

#### 6.1 Conclusion

The main purpose of this study is to create a model which will detect the breast cancer depending on histopathology and MRI image. I try CNN and three pre-trained model VGG-16, Inception V3 & ResNet50 for both datasets. For histopathology image dataset VGG-16 achieve maximum accuracy of 99.32%. and for MRI image dataset Inception V3 achieve more accuracy of 95.36%. Here the histopathology image dataset consists of total 7909 images which is a large dataset. On the other hand, the MRI dataset contain only 780 images. My main purpose for using CNN is, this is one of the most efficient deep learning methods for image classification. In the future, I will work for the improvement of the prediction results and also try the other pre-trained models for better performance.

#### 6.2 Recommendation for Future Study

In this study I work with only two type of images such as histopathology and MRI image. But there are others way to detect the breast cancer. Working for those fields is needed. In this study the MRI dataset was a small dataset. In future I will try work with a big MRI dataset to achieve more accuracy and a better model. I am also trying to develop a single page web application for the implementation of my project.

## **References:**

- [1] Rawal, Ramik. "Breast cancer prediction using machine learning." *Journal of Emerging Technologies and Innovative Research (JETIR)* 13, no. 24 (2020): 7.
- [2] Li, Yixuan, and Zixuan Chen. "Performance evaluation of machine learning methods for breast cancer prediction." *Appl Comput Math* 7, no. 4 (2018): 212-216.
- [3] Altameem, Ayman, Chandrakanta Mahanty, Ramesh Chandra Poonia, Abdul Khader Jilani Saudagar, and Raghvendra Kumar. "Breast Cancer Detection in Mammography Images Using Deep Convolutional Neural Networks and Fuzzy Ensemble Modeling Techniques." *Diagnostics* 12, no. 8 (2022): 1812.
- [4] Spanhol, Fabio A., Luiz S. Oliveira, Caroline Petitjean, and Laurent Heutte. "A dataset for breast cancer histopathological image classification." *Ieee transactions on biomedical engineering* 63, no. 7 (2015): 1455-1462.
- [5] Al-Dhabyani, Walid, Mohammed Gomaa, Hussien Khaled, and Aly Fahmy. "Dataset of breast ultrasound images." *Data in brief* 28 (2020): 104863.
- [6] Nallamala, Sri Hari, Pragnyaban Mishra, and Suvarna Vani Koneru. "Breast cancer detection using machine learning way." *Int J Recent Technol Eng* 8, no. 2-3 (2019): 1402-1405.
- [7] Tahmooresi, M., A. Afshar, B. Bashari Rad, K. B. Nowshath, and M. A. Bamiah. "Early detection of breast cancer using machine learning techniques." *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)* 10, no. 3-2 (2018): 21-27.
- [8] Asri, Hiba, Hajar Mousannif, Hassan Al Moatassime, and Thomas Noel. "Using machine learning algorithms for breast cancer risk prediction and diagnosis." *Procedia Computer Science* 83 (2016): 1064-1069.
- [9] Couture, Heather D., Lindsay A. Williams, Joseph Geradts, Sarah J. Nyante, Ebonee N. Butler, J. S. Marron, Charles M. Perou, Melissa A. Troester, and Marc Niethammer. "Image analysis with deep learning to predict breast cancer grade, ER status, histologic subtype, and intrinsic subtype." *NPJ breast cancer* 4, no. 1 (2018): 1-8.
- [10] Nasir, Muhammad Umar, Taher M. Ghazal, Muhammad Adnan Khan, Muhammad Zubair, Atta-ur Rahman, Rashad Ahmed, Hussam Al Hamadi, and Chan Yeob Yeun. "Breast Cancer Prediction Empowered with Fine-Tuning." *Computational Intelligence and Neuroscience* 2022 (2022).
- [11] Giri, Prannoy, and K. Saravanakumar. "Breast cancer detection using image processing techniques." *Oriental journal of computer science and technology* 10, no. 2 (2017): 391-399.



## Appendix

### Appendix A: Research Reflection

During this research, I face many problems. Like collecting and selecting the datasets. I had to learn many things as machine learning, deep learning, FastAPI & python. Particularly convolutional neural network and vgg-16.

### Appendix B: Related issue

In figure B1 I have shown the imported libraries.

```
import tensorflow as tf
from tensorflow.keras import models, layers
from tensorflow.keras.layers import Input, Flatten, Dense
from tensorflow.keras.models import Model
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.applications.inception_v3 import InceptionV3
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.models import Sequential
from glob import glob
import os
import cv2
import random
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

Figure B1: Imported libraries

In figure B2 I have shown some pre-set parameters. Those parameters are set for both histopathology and MRI images.

```
IMG_SIZE = 224
BATCH_SIZE = 32
CHANNELS = 3
EPOCH = 20
```

Figure B2: Pre-set parameters

In B3 & B4 I have shown the data splitting for both histopathology and MRI images. Where I split the data into 3 parts. 80% for training, 10% for validation and 10% for testing.

```
training data = 80% ; validation data = 10% ; testing data = 10%
```

```
def dataset_partition(ds, train_split=0.8, val_split=0.1, test_split=0.1, shuffle=True):  
    ds_size = len(ds)  
    if shuffle:  
        ds = ds.shuffle(shuffle_size, seed=12)  
    train_size = int(train_split * ds_size)  
    val_size = int(val_split * ds_size)  
    train_ds = ds.take(train_size)  
    val_ds = ds.skip(train_size).take(val_size)  
    test_ds = ds.skip(train_size).skip(val_size)  
    return train_ds, val_ds, test_ds
```

```
train_ds, val_ds, test_ds = dataset_partition(dataset)
```

```
len(train_ds)
```

```
198
```

```
len(val_ds)
```

```
24
```

```
len(test_ds)
```

```
26
```

Figure B3: Data splitting for histopathology images

training data = 80% ; validation data = 10% ; testing data = 10%

```
def dataset_partition(ds, train_split=0.8, val_split=0.1, test_split=0.1, shuffle=True):  
    ds_size = len(ds)  
  
    if shuffle:  
        ds = ds.shuffle(shuffle_size, seed=12)  
  
    train_size = int(train_split * ds_size)  
    val_size = int(val_split * ds_size)  
  
    train_ds = ds.take(train_size)  
    val_ds = ds.skip(train_size).take(val_size)  
    test_ds = ds.skip(train_size).skip(val_size)  
  
    return train_ds, val_ds, test_ds
```

```
train_ds, val_ds, test_ds = dataset_partition(dataset)
```

```
len(train_ds)
```

20

```
len(val_ds)
```

2

```
len(test_ds)
```

3

Figure B4: Data splitting for MRI images

In figure B5 I have shown the image resize and rescale process for both histopathology and MRI images.

```
resize_and_rescale = tf.keras.Sequential([  
    layers.experimental.preprocessing.Resizing(IMG_SIZE, IMG_SIZE),  
    layers.experimental.preprocessing.Rescaling(1.0/255)  
])
```

Figure B5: Image resizing and rescaling

In figure B6 & B7 I have shown the both CNN architecture for histopathology and MRI models.

```
input_shape = (BATCH_SIZE, IMG_SIZE, IMG_SIZE, CHANNELS)
n_classes = 2

model = models.Sequential([
    resize_and_rescale,

    layers.Conv2D(32, (3, 3), activation='relu', input_shape=input_shape),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, kernel_size= (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, kernel_size= (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(n_classes, activation='softmax')
])

model.build(input_shape=input_shape)

model.summary()

...

model.compile(
    optimizer='adam',
    loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=False),
    metrics=['accuracy']
)
```

Figure B6: CNN architecture of histopathology model

```

input_shape = (BATCH_SIZE, IMG_SIZE, IMG_SIZE, CHANNELS)
n_classes = 3

model = models.Sequential([
    resize_and_rescale,

    layers.Conv2D(32, (3, 3), activation='relu', input_shape=input_shape),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, kernel_size=(3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, kernel_size=(3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),

    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(n_classes, activation='softmax')
])

model.build(input_shape=input_shape)

model.compile(
    optimizer='adam',
    loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=False),
    metrics=['accuracy']
)

```

Figure B7: CNN architecture of MRI model

In figure B8 & B9 I have shown CNN training of both histopathology and MRI models.

```
history = model.fit(
    train_ds,
    epochs=EPOCH,
    batch_size=BATCH_SIZE,
    verbose=1,
    validation_data=val_ds
)
```

Epoch 1/20  
198/198 [=====] - 292s 1s/step - loss: 0.5332 - accuracy: 0.7390 - val\_loss: 0.4332 - val\_accuracy: 0.8190  
Epoch 2/20  
198/198 [=====] - 190s 959ms/step - loss: 0.4532 - accuracy: 0.8182 - val\_loss: 0.3840 - val\_accuracy: 0.8620  
Epoch 3/20  
198/198 [=====] - 186s 941ms/step - loss: 0.4413 - accuracy: 0.8241 - val\_loss: 0.3772 - val\_accuracy: 0.8581  
Epoch 4/20  
198/198 [=====] - 186s 939ms/step - loss: 0.4060 - accuracy: 0.8432 - val\_loss: 0.3723 - val\_accuracy: 0.8477  
Epoch 5/20  
198/198 [=====] - 187s 945ms/step - loss: 0.3919 - accuracy: 0.8471 - val\_loss: 0.3382 - val\_accuracy: 0.8815  
Epoch 6/20  
198/198 [=====] - 185s 934ms/step - loss: 0.3893 - accuracy: 0.8527 - val\_loss: 0.3322 - val\_accuracy: 0.8763  
Epoch 7/20  
198/198 [=====] - 187s 944ms/step - loss: 0.3746 - accuracy: 0.8607 - val\_loss: 0.3783 - val\_accuracy: 0.8398  
Epoch 8/20  
198/198 [=====] - 189s 952ms/step - loss: 0.3659 - accuracy: 0.8648 - val\_loss: 0.3699 - val\_accuracy: 0.8438  
Epoch 9/20  
198/198 [=====] - 188s 950ms/step - loss: 0.3555 - accuracy: 0.8663 - val\_loss: 0.5143 - val\_accuracy: 0.7708  
Epoch 10/20  
198/198 [=====] - 187s 945ms/step - loss: 0.3524 - accuracy: 0.8647 - val\_loss: 0.3440 - val\_accuracy: 0.8750

Figure B8: CNN model training for histopathology image

```
history = model.fit(  
    train_ds,  
    epochs=EPOCH,  
    batch_size=BATCH_SIZE,  
    verbose=1,  
    validation_data=val_ds  
)
```

```
Epoch 1/20  
20/20 [=====] - 27s 1s/step - loss: 1.0157 - accuracy:  
0.5435 - val_loss: 0.9615 - val_accuracy: 0.6250  
Epoch 2/20  
20/20 [=====] - 20s 1s/step - loss: 0.9761 - accuracy:  
0.5435 - val_loss: 0.8459 - val_accuracy: 0.6250  
Epoch 3/20  
20/20 [=====] - 20s 1s/step - loss: 0.9412 - accuracy:  
0.5452 - val_loss: 0.7793 - val_accuracy: 0.6250  
Epoch 4/20  
20/20 [=====] - 20s 1s/step - loss: 0.8710 - accuracy:  
0.5968 - val_loss: 0.7462 - val_accuracy: 0.6562  
Epoch 5/20  
20/20 [=====] - 20s 1s/step - loss: 0.8459 - accuracy:  
0.6161 - val_loss: 0.7378 - val_accuracy: 0.6250  
Epoch 6/20  
20/20 [=====] - 20s 1s/step - loss: 0.8274 - accuracy:  
0.6194 - val_loss: 0.6789 - val_accuracy: 0.7031  
Epoch 7/20  
20/20 [=====] - 20s 1s/step - loss: 0.7657 - accuracy:  
0.6403 - val_loss: 0.6695 - val_accuracy: 0.7031  
Epoch 8/20  
20/20 [=====] - 20s 1s/step - loss: 0.7358 - accuracy:  
0.6548 - val_loss: 0.6413 - val_accuracy: 0.7031  
Epoch 9/20  
20/20 [=====] - 20s 1s/step - loss: 0.6643 - accuracy:  
0.6726 - val_loss: 0.5549 - val_accuracy: 0.7188  
Epoch 10/20  
20/20 [=====] - 20s 1s/step - loss: 0.6520 - accuracy:  
0.7177 - val_loss: 0.5581 - val_accuracy: 0.7656
```

Figure B9: CNN model training for MRI image

## Proj\_Rep

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