

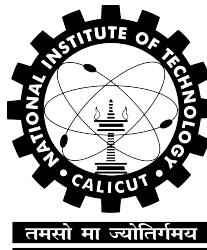
**Breast Cancer Histology Images Classification using  
Convolutional Neural Networks  
CS4090 Project  
Final Report**

*Submitted by*

Ch Prudhvi Sairam (B160555CS)  
G Hemanthnath Chowdary (B160747CS)  
J Vishnu Vardhan Sai (B160733CS)

*Under the Guidance of*

**Dr. Abdul Nazeer K A**

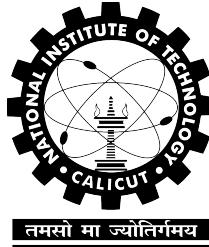


**Department of Computer Science and Engineering  
National Institute of Technology Calicut  
Calicut, Kerala, India - 673 601**

**June, 2020**

**NATIONAL INSTITUTE OF TECHNOLOGY CALICUT  
KERALA, INDIA - 673 601**

**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**



**CERTIFICATE**

*Certified that this is a bonafide report of the project work titled*

**BREAST CANCER HISTOLOGY IMAGES CLASSIFICATION  
USING CONVOLUTIONAL NEURAL NETWORKS**

*done by*

**Ch Prudhvi Sairam  
G Hemanthnath Chowdary  
J Vishnu Vardhan Sai**

*of Eighth Semester B. Tech, during the Winter Semester 2019-'20, in  
partial fulfillment of the requirements for the award of the degree of  
Bachelor of Technology in Computer Science and Engineering of the  
National Institute of Technology Calicut.*

	Dr. Abdul Nazeer K A	
14 June 2020	<b>Professor</b>	Dr. Saleena N
<b>Date</b>	<b>Project Guide</b>	<b>Head of the Department</b>

# **DECLARATION**

I hereby declare that the project titled, **Breast Cancer Histology Images Classification using Convolutional Neural Networks** is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or any other institute of higher learning, except where due acknowledgement and reference has been made in the text.

Place :

Date : 14 June 2020

Signature :

Name : Ch.Prudhvi Sairam

Roll. No. : B160555CS

Name : J Vishnu Vardhan Sai

Roll.No. : B160733CS

Name : G.Hemanthnath Chowdary

Roll.No. : B160747CS

## **Abstract**

Breast Cancer is the second most (after skin cancer) common type of cancer that leads to death in women around the world. It is a disease in which cancer cells form in the tissues of the breast. Our problem is to classify the H&E stained breast histology microscopic images in to four classes: NORMAL, BENIGN, IN-SITU carcinoma and INVASIVE carcinoma using various combinations of already trained convolutional neural networks (transfer learning) with high accuracy. CNNs are already proven to be good in image classification problems of various domains and in medical image classification problems also. In this project we will present three CNN models which are trained on Densenet-201 architecture. We have applied different preprocessing techniques like colour normalization and dividing images into patches for the input dataset. We have achieved good accuracy score of 88% from these models by applying majority voting scheme. This will automate the manual work of classifying the histology images which has been time taking task in the past.

## **ACKNOWLEDGEMENT**

First of all we would like to express our gratitude to Dr. Abdul Nazeer K A, Professor of CSE Department, National Institute of Technology Calicut, for helping us all the time for completing this project.

We are also thankful to our project panel members Dr.Gopakumar G Assistant Professor, Department of CSE, NIT Calicut and Dr. Jayaraj P B Assistant Professor, Department of CSE, NIT Calicut for their valuable suggestions.

We would also personally like to thank Jeremy Howard, Deep learning researcher at fast.ai and University of San Francisco for his MOOCs on Deep Learning with fastai helped us to great extent.

We would also like to thank everyone who is contributing to Deep Learning and Computer Vision for making the world a better place.

# Contents

<b>1</b>	<b>Introduction</b>	<b>2</b>
1.1	Breast Cancer . . . . .	2
1.2	Convolutional Neural Network . . . . .	3
<b>2</b>	<b>Literature Survey</b>	<b>7</b>
2.1	Literature Review . . . . .	7
2.1.1	Related Work on Classification . . . . .	8
<b>3</b>	<b>Problem Definition</b>	<b>11</b>
3.1	Motivation . . . . .	11
3.2	Input and Output . . . . .	11
<b>4</b>	<b>Methodology</b>	<b>13</b>
4.1	Data Description . . . . .	13
4.2	Design . . . . .	14
4.2.1	Pre-processing . . . . .	14
4.2.2	Training and Classification . . . . .	15
<b>5</b>	<b>Results</b>	<b>17</b>
5.1	Original dataset . . . . .	17
5.2	Our extended dataset . . . . .	17
5.3	Trained models . . . . .	18
5.3.1	Original Data . . . . .	18
5.3.2	Colour-Normalized . . . . .	19
5.3.3	Patches . . . . .	20
5.3.4	Majority Voting Architecture . . . . .	21
<b>6</b>	<b>Conclusion</b>	<b>23</b>
6.1	Summary . . . . .	23
6.2	Future work . . . . .	23
	<b>References</b>	<b>23</b>

# List of Figures

1.1	Multilayer Perceptron[12] . . . . .	4
1.2	Position of cat changes the weights of connections in MLP[12]	4
1.3	Architecture of a standard CNN[12] . . . . .	5
2.1	A:Normal, B:Benign[4] . . . . .	8
2.2	A:In-situ, B:Invasive[4] . . . . .	8
4.1	A:Source image, B:Target image, C:After normalization . . .	14
4.2	Corresponding augmented images . . . . .	15
5.1	Confusion matrix for ResNet50 . . . . .	18
5.2	Confusion matrix for DenseNet169 . . . . .	19
5.3	Confusion matrix for DenseNet201 . . . . .	19
5.4	Confusion matrix for DenseNet201 with Colour-Normalized data	20
5.5	Confusion matrix for DenseNet201 with data of patches . . .	21
5.6	Majority Voting Architecture with 3 pre-trained Densenet-201 models. . . . .	22

# Chapter 1

## Introduction

### 1.1 Breast Cancer

Cancer is a term for a class of diseases characterized by abnormal cells that grow in tissues and invade healthy cells in the body. Abnormal cells means the cells that are unusual in function. Breast cancer starts in the cells of the breast as a group of cancer cells that can then invade surrounding tissues or spread to other areas of the body.

A tumour is an abnormal growth of cells that serves no purpose. There are two types of tumours:

1. Benign
2. Malignant

Benign tumour means there is no possibility of spreading the cancer cells to the other tissues. Malignant tumour refers to where the cancer cells move and spread to the other tissues. Although breast cancer most commonly spreads to nearby lymph nodes, it can also spread further through the body to areas such as the bones, lungs, liver, and brain.

In case of breast cancer malignant tumour is of two types:

1. Ductal carcinoma insitu(DCIS)
  - This stays within the milk ducts or lobules in the breast. They do not grow into or invade normal tissues within or beyond the breast.

## 2. Invasive ductal carcinoma(IDC)

- These cancers do grow into normal, healthy tissues. Most breast cancers are invasive.

These malignant forms consists of stages about extension and spreading of tumour cancer cells to some parts of the body. The healthcare team will determine breast cancer staging to communicate how far the disease has progressed.

Although cancer is dangerous with the development of the medical imaging equipment we have witnessed a rise in the number of people who are diagnosed with breast cancer, the number of deaths is significantly decreased amongst all the ranges of age.

## 1.2 Convolutional Neural Network

The **Universal approximation theorem** essentially states if a problem can be solved it can be solved by deep neural networks, given enough layers of affine functions layered with non-linear functions. Essentially a stack of linear functions followed by non-linear functions could solve any problem that is solvable.

### The problem with traditional neural networks in image classification

Multilayer perceptron (MLP) is a traditional neural network which is designed based on inspiration from brain. It looks like as shown in figure 1.1

There are several drawbacks of MLP's, especially when it comes to image processing. MLPs use one perceptron for each input (e.g. pixel in an image, multiplied by 3 in RGB case). The amount of weights rapidly becomes unmanageable for large images. For a 224 x 224 pixel image with 3 color channels there are around 150, 000 weights that must be trained. As a result, difficulties arise whilst training and overfitting can occur [3].

Another common problem is that MLPs react differently to an input (images) and its shifted version — they are not translation invariant. For example, if a picture of a cat appears in the top left of the image in one

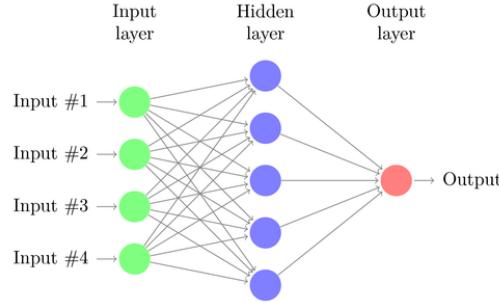


Figure 1.1: Multilayer Perceptron[12]

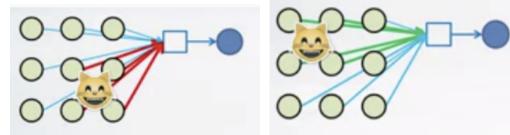


Figure 1.2: Position of cat changes the weights of connections in MLP[12]

picture and the bottom right of another picture, the MLP will try to correct itself and assume that a cat will always appear in this section of the image. Clearly, MLPs are not the best idea to use for image processing. One of the main problems is that spatial information is lost when the image is flattened into an MLP. Nodes that are close together are important because they help to define the features of an image. We thus need a way to leverage the spatial correlation of the image features (pixels) in such a way that we can see the cat in our picture no matter where it may appear.

### What is CNN?

A convolutional neural network[3] mainly consist of 3 layers:

1. Convolutional Layer

- Convolutional layers are the layers where filters are applied to the original image, or to other feature maps in a deep CNN. This is where most of the user-specified parameters are in the network. The most important parameters are the number of kernels and the size of the kernels [2].

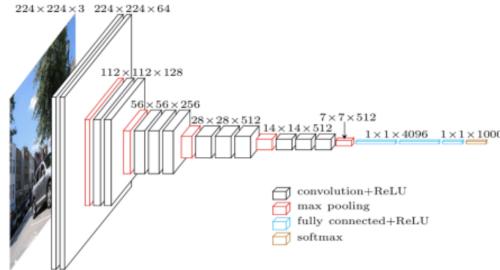


Figure 1.3: Architecture of a standard CNN[12]

## 2. Pooling Layer

- Pooling layers are similar to convolutional layers, but they perform a specific function such as max pooling, which takes the maximum value in a certain filter region, or average pooling, which takes the average value in a filter region. These are typically used to reduce the dimensionality of the network.

## 3. Fully Connected Layer

- Fully connected layers are placed before the classification output of a CNN[3] and are used to flatten the results before classification. This is similar to the output layer of an MLP.

## How CNN solve problem of MLP in Image Classification?

CNN's[3] leverage the fact that nearby pixels are more strongly related than distant ones. We analyze the influence of nearby pixels by using something called a filter. A filter is exactly what you think it is, in our situation, we take a filter of a size specified by the user and we move this across the image from top left to bottom right [2]. For each point on the image, a value is calculated based on the filter using a convolution operation. A filter could be related to anything, for pictures of humans, one filter could be associated with seeing noses, and our nose filter would give us an indication of how strongly a nose seems to appear in our image, and how many times and in what locations they occur. This reduces the number of weights that the neural network must learn compared to an MLP, and also means that when

the location of these features changes it does not throw the neural network off. Different filters can be used to extract different features of an image for example we use two different kind of filters to detect horizontal edges and vertical edges. Once trained these filters can detect what they supposed to detect irrespective of the position in the image. Thus, CNN's[3] can be used to solve most of our problems.

# Chapter 2

## Literature Survey

### 2.1 Literature Review

Breast cancer diagnosis usually consists in an initial detection via palpation and regular check-ups using mammography or ultrasound imaging. The diagnosis is then followed by breast tissue biopsy if the check-up exam indicates the possibility of malignant tissue growth. Breast tissue biopsies allow the pathologists to histologically assess the microscopic structure and elements of the tissue [1]. The histology allows to distinguish between normal tissue, non-malignant (benign) and malignant lesions and to perform a prognostic evaluation. Benign lesions represent changes in normal structures of breast parenchyma that are not directly related with progression to malignancy. Carcinomas can be classified as *in situ* or invasive. In *in situ* carcinoma the cells are restrained inside the mammary ductal-lobular system, whereas in invasive carcinoma the cells spread beyond that structure. The tissue collected during the biopsy is commonly stained with hematoxylin and eosin (H&E) prior to the visual analysis performed by the specialists. During this procedure, relevant regions of whole-slide tissue scans are assessed [5] . Fig 2.1, 2.2 shows an example of patches from whole slide images stained with H&E for each of the classes mentioned. The staining enhances nuclei (purple) and cytoplasm (pinkish), as well as other structures of interest. During the analysis of the stained tissue, pathologists analyze overall tissue architecture, along with nuclei organization, density and variability. For instance, tissues with invasive carcinoma show a distortion of the architecture as well as higher nuclei density and variability (Fig 2.2-B), whereas in normal tissue

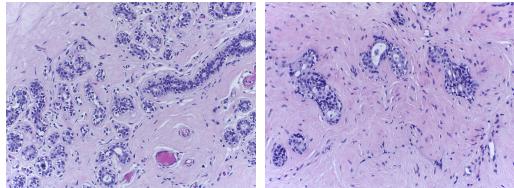


Figure 2.1: A:Normal, B:Benign[4]

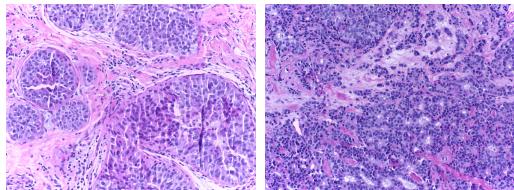


Figure 2.2: A:In-situ, B:Invasive[4]

the architecture is maintained and the nuclei are well organized (Fig 2.1-A). The diagnosis process using H&E stained biopsies is not trivial, and the average diagnostic concordance between specialists is approximately 75% . The manual examination of histology images requires intense workload of highly specialized pathologists. The subjectivity of the application of morphological criteria in usual classification motivates the use of computer aided diagnosis (CAD) systems to improve the diagnosis efficiency and increase the level of inter-observer agreement [6].

So these obtained and H&E stained histology images can be classified using several CNN architectures and we can predict the relevant class better than accuracy of specialist(75%). This automated models can reduce the critical work of specialist and also increases accuracy.

### 2.1.1 Related Work on Classification

The classification of breast histology images as benign-malignant for referral purpose is vastly addressed topic. Over the past decade, these methods have focused on extraction of nuclei features, which require the detection of regions-of-interest. For example, nuclei have been segmented via colour-based clustering Kowal et al.[7] or by nuclei candidate detection using the circular Hough transform, followed by feature-based candidate reduction and refinement via watersheds George et al.[8]. These segmentations allow to extract

features, usually related to morphology, topology, texture. The computed features then be used for training one or more classifiers and allow to achieve accuracies of 84-93% Kowal et al.[7] and 72-97% George et al.[8].

A alternative to the design and extraction of hand-crafted features is to use deep learning approaches, namely CNNs, since these allow to significantly reduce field work while achieving similar or better results. Spanhol et al.[9].They uses CNNs to classify microscopy images and make predictions on BreaKHis dataset which contain images at different magnifications. They got accuracy of 84% for 200 X magnification.

The more complex 3-class problem of considering normal tissue, *in situ* carcinoma and invasive carcinoma has also been addressed by the scientific community. Due to the increased complexity of the task, using nuclei-related features is usually not enough to achieve a reasonable classification performance. Namely, distinguishing *in situ* and invasive carcinomas requires assessing both the nuclei and their organization on the tissue. For instance, He et al.[2] used a cascade classification approach , where features based on the curvelet transform and local binary patterns were randomly chosen as input to a set of parallel support-vector machines (SVMs) [2]. The images where no agreement was found were analysed by a set of NNs using another random feature set, resulting in an accuracy of 97%.

Despite the successes for 2-class and 3-class classifications, few works have addressed the 4-classification problem (normal tissue, benign, *insitu* and invasive carcinoma) of histology images. Most recent works on 4 classification problem are stated below

Chennamsetty et al.[10] used an ensemble of ImageNet pre-trained CNNs to classify the images from microscopy histology images (BACH 2018 Dataset). Specifically, the algorithm is composed of a ResNet-101 He et al.[2] and two DenseNet-161 Huang et al.[3] networks fine-tuned with images from varying data normalization schemes. Initializing the model with pre-trained weights alleviates the problem of training the networks with limited amount of high-quality labelled data. First, the images were resized to 224 \*224 pixels via bilinear interpolation and normalized to zero mean and unit standard deviation according to statistics derived either from ImageNet or Part A datasets, as detailed below. During training, the ResNet-101 and a DenseNet-161 were fine-tuned with images normalized from the breast histology data whereas the other DenseNet-161 was fine-tuned with the ImageNet normalization. Then, for inference, each model in the ensemble predicts the cancer grade in the

input image and a majority voting scheme is posteriorly used for assigning the class associated with the input.

Brancati et al. [11] proposed a deep learning approach based on a fine-tuning strategy by exploiting transfer learning on an ensemble of ResNet He et al.[2] models. ResNet was preferred to other deep network architectures because it has a small number of parameters and shows a relatively low complexity in comparison to other models. The authors opted by further reducing the complexity of the problem by down sampling the image by factor  $k$  and using only the central patch of size  $m * m$  as input to the network. In particular,  $k$  was fixed to 80% of the original image size and  $m$  was set equal to the minimum size between the width and high of the resized image. The proposed ensemble is composed of 3 ResNet configurations: 34, 50 and 101. Each configuration was trained on the Microscopy images and the classification of a test image is obtained by computing the highest-class probability provided by the three configurations.

Aditya golatkar et al.[1] proposed a classification of the H&E tissue images in four classes normal, benign, in situ, and invasive. They used transfer learning for training the patch-level classifier with a large neural network architecture (Inception-v3) by using weights pretrained on ImageNet dataset .They have achieved a classification accuracy of 79% at patch-level. The image-level classification was done by majority-voting over patch-level classification results, resulting in an average accuracy of 85% over the four classes and carcinoma versus non-carcinoma classification accuracy of 93% .

# Chapter 3

## Problem Definition

To develop a convolutional neural network model with good accuracy score to classify the H&E stained breast histology microscopic images in to four classes: NORMAL, BENIGN, IN-SITU carcinoma and INVASIVE carcinoma classes.

### 3.1 Motivation

Breast cancer is one of the leading causes of deaths across the world in women. Early diagnosis of this type of cancer is critical for treatment and patient care. Manual assessment of large scale histopathological images is a challenging task due to variations in appearance, structure and textures. Such a manual analysis is time intensive and often dependent on subjective human interpretation. So, to make this manual process of detecting malignant tumors automatic, CNN models have been trained to classify the histopathological images.

### 3.2 Input and Output

#### Input

Input consists of images from the Dataset of BACH 2018 challenge. These images are Hematoxylin&Eosin(H&E) stained images they are gathered from different sources and put together to form this dataset. The dataset contains

400 images belonging to 4 different classes Normal, Benign, In-Situ, Invasive each of 100 images.

- Color model: R(ed)G(reen)B(lue)
- Size: 2048 x 1536 pixels
- Memory space: 10-20 MB (approx.)
- Type of label: image-wise

## Output

Input image will be preprocessed using different techniques like colour normalization and dividing the image into patches. After that, the image will be passed through three trained CNN models. The output class of image is obtained by applying majority voting scheme to the three CNN models. Output will be one of the four classes Normal, Benign, In-Situ or Invasive

# Chapter 4

## Methodology

### 4.1 Data Description

In this section we will be introducing the dataset we will be using in our project [4]. The dataset consists of H&E stained breast histology microscopy images in four classes: normal, benign, in situ carcinoma and invasive carcinoma.

The dataset contains a total of 400 microscopy images, distributed as follows:

- Normal: 100
- Benign: 100
- In situ carcinoma: 100
- Invasive carcinoma: 100

Microscopy images have the following specifications:

- Color model:R(ed)G(reen)B(lue)
- Size:2048 x 1536 pixels

## 4.2 Design

### 4.2.1 Pre-processing

#### Color Normalization

Stain inconsistency of histology images, due to differences in color responses of slide digital scanners, will affect the performance of image analysis. As can be seen from Fig. 4.1 A and Fig. 4.1 B the images in the dataset have large stain variation. To this end, stain normalization is essential prior to other processes. There are various research for stain normalization in histology images. In this project we are using a method proposed by Reinhard, which transforms the RGB images to the  $L^*a^*b^*$  color space, followed by utilizing the means and standard deviations for each channel separately in  $L^*a^*b^*$  colour space and finally, converts the results back to RGB. Fig. 4.1 C illustrates the effect of the method on a breast histology image.

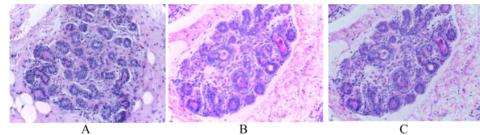


Figure 4.1: A:Source image, B:Target image, C:After normalization

#### Division of images into patches

Every cnn architecture that has been pre-trained with a dataset has input image size of 299 x 299 pixels or 244 x 244 pixels, but our dataset consists of images with resolution of 2048 x 1536 pixels. If we train a cnn model with our dataset without doing any resizing or dividing it into patches, we may lose the nuclei level information and due to that loss of information, accuracy will be decreased. So, we will divide each image in our dataset into patches of different sizes to contain the global tissue structures information and nuclei level information. All extracted patches are given the same label as the corresponding histology image.

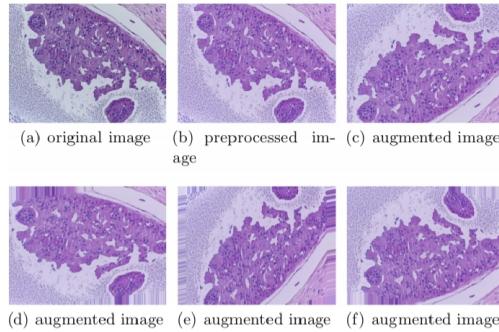


Figure 4.2: Corresponding augmented images

### Data augmentation

After the patch extraction process, dataset contains 14000 patches. Now we will apply data augmentation to each patch by either rotating or flipping the patch at different angles. After applying the data augmentation, each patch will be transformed into more patches, as seen in Fig 4.2. Now, the dataset consists of 1,00,000 patches, approximately.

### Resizing the patches

As every CNN architecture is pretrained on some fixed size images(ex: 224 x 224 pixels or 299 x 299 pixels) and it will be hard to train on a very large size images We will be resizing the patches into 224 x 224 pixels or 299 x 299 pixels according to cnn architecture.

## 4.2.2 Training and Classification

### Training

After patch extraction and data augmentation we have a lot of data which will be good to get a model with good accuracy score. Here we train 3 models (RESNET152, DENSENET169, DENSENET201) on all the data we created using transfer learning technique.

After dividing the images into patches, we will train the CNN model with that patches as input data. As CNN architectures are pre trained with different dataset, we will remove fully connected layer and softmax layer.

Now, we will add new fully connected layer and a softmax layer with four output neurons. While training the model, First we will freeze some layers and train the model. Next, we will unfreeze all the layers and train the model.

### Classification

**1.Patch wise classification** In patch wise classification, each stained microscopy image is divided into patches. These patches are preprocessed and resized according to the CNN architecture. Now, these patches are classified using model trained using the training data.

**2.Image wise classification** We combined the patch-based predictions using majority voting to determine the class of the entire image. In majority voting, the class of the entire image is the class to which maximum number of patches extracted from that image belong[5].

### Tuning

Repeating preprocessing and training with different image sizes and different CNN model combinations until we get the best accuracy possible.

# Chapter 5

# Results

## 5.1 Original dataset

The image dataset consists of 400 H&E stain images (2048 x 1536 pixels) was performed by two medical experts, with pixel scale 0, 42 m. The images were evenly sampled from each classes: Normal (100), Benign (100), In-situ carcinoma (100) and Invasive carcinoma (100)[4]. The patient-wise origin of each microscopy image is only partially available due to the anonymization process. The test set with 100 microscopy images was private and internally used for ranking submitted solutions.

## 5.2 Our extended dataset

To enrich training set from original dataset (400 images), we have divided every image into patches to increase the data as cnn model requires large amount of data. So, after this divison of images into patches we got around 14000 images. As every cnn architecture is pretrained on some fixed size images. We will resize our patches to 299 x 299 pixels or 244 x 244 pixels according to the cnn architecture. We also applied colour normalization technique to the initial 400 images to reduce the stain variation.

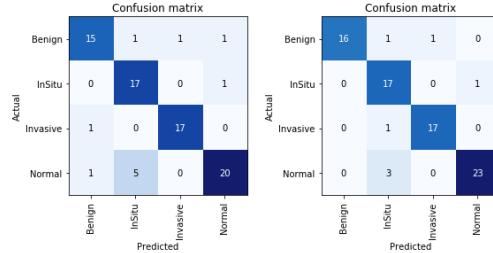


Figure 5.1: Confusion matrix for ResNet50

### 5.3 Trained models

We have trained original dataset on three cnn networks (RESNET50, DENSENET169, DENSENET201). We have trained the networks for 60 epochs. We have got accuracy around 80% for Resnet50 on the test dataset of 100 images and accuracy around 81% for Densenet169 and Densenet201 for the test dataset. Fig 5.1, 5.2, 5.3 shows the confusions matrices for the three models trained respectively.

#### 5.3.1 Original Data

##### Model 1: ResNet50

- Epochs : 60 (Unfreeze) + 60 (freeze)
- Image Size : 299\*299
- Accuracy achieved : 80 (On Test Dataset)

##### Model 2: DenseNet169

- Epochs : 60 (Unfreeze) + 60 (freeze)
- Image Size : 299\*299
- Accuracy achieved : 81 (On Test Dataset)

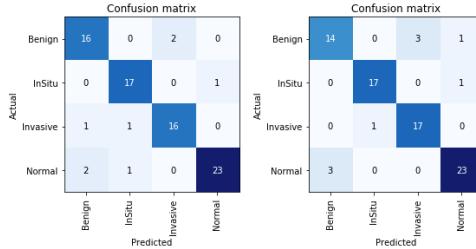


Figure 5.2: Confusion matrix for DenseNet169

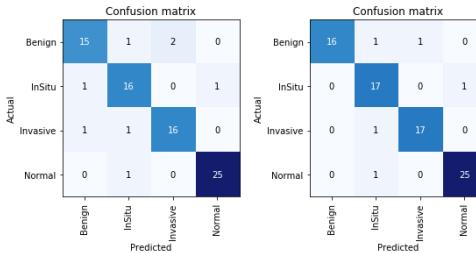


Figure 5.3: Confusion matrix for DenseNet201

### Model 3: DenseNet201

- Epochs : 60 (Unfreeze) + 60 (freeze)
- Image Size : 299\*299
- Accuracy achieved : 81 (On Test Dataset)

#### 5.3.2 Colour-Normalized

Now, we have applied colour normalization to our original dataset of 400 images to reduce the stain variation. We have trained this data on Densenet201 cnn model for 90 epochs. We have got an accuracy of 84% for the test dataset of 100 images. Fig 5.4 depicts the confusion matrix for the cnn model trained.

### Model 1: DenseNet201

- Epochs : 90 (Unfreeze) + 90 (freeze)

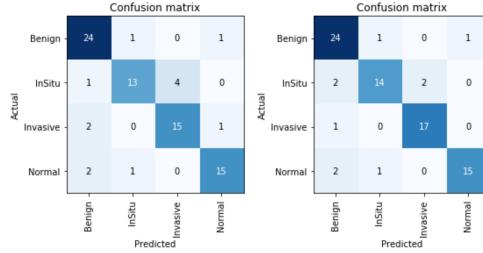


Figure 5.4: Confusion matrix for DenseNet201 with Colour-Normalized data

- Image Size : 299\*299
- Accuracy achieved : 84 (On Test Dataset)

### 5.3.3 Patches

Here we divided the each image in to 35 patches. Each patch is of size 512px\*512px. We applied stride of 256px on original image, while dividing it into patches. Each patch is labelled with the original image label. After dividing all 400 images into patches, we got 14000 images. Out of these 14000 images, 10500 are used for training and remaining 3500 for validation. Now, densenet201 model is trained on these 10500 patches and validated on the remaining 3500 patches.

#### Model 1: DenseNet201

- Epochs : 50 (Unfreeze) + 50 (freeze)
- Image Size : 299\*299
- Accuracy achieved : 86 (On Test Dataset)

We have trained Densenet201 model with 10500 images after dividing the original images into patches. we have trained this data on Densenet201 CNN model for 50 epochs. we have got an accuracy of 86% for the test dataset of 100 images.Fig 5.5 depicts the confusion matrix for the CNN model trained.

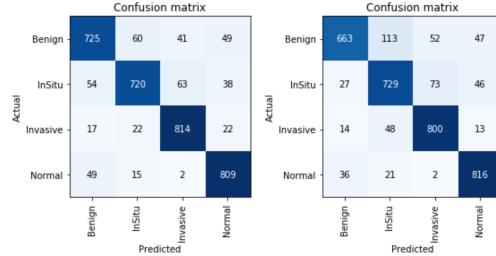


Figure 5.5: Confusion matrix for DenseNet201 with data of patches

### 5.3.4 Majority Voting Architecture

We have trained 3 CNN models with DenseNet-201 architecture. We have trained the first CNN model with original dataset and we got accuracy of 81%. The second CNN model has been trained with dataset that has been preprocessed with colour normalization technique. We got accuracy of 84% for the second model. The third CNN model has been trained with a dataset where we have divided original images into patches. We have got around 14000 patches from the images. After training the CNN model with this dataset, we got accuracy of 86%. Now, we have applied majority voting for all these three CNN models which works as follows:

Given a test image it will be predicted by all the pretrained models as shown in the Fig:5.6 then the best of the three models will be selected to predict the output. If all the models predict different output then the output given by the model that is trained on patches will be taken because it has higher accuracy than the other 2 models. This method improves our accuracy by 2% we got accuracy of 88% by doing majority voting.

- Accuracy : 88%

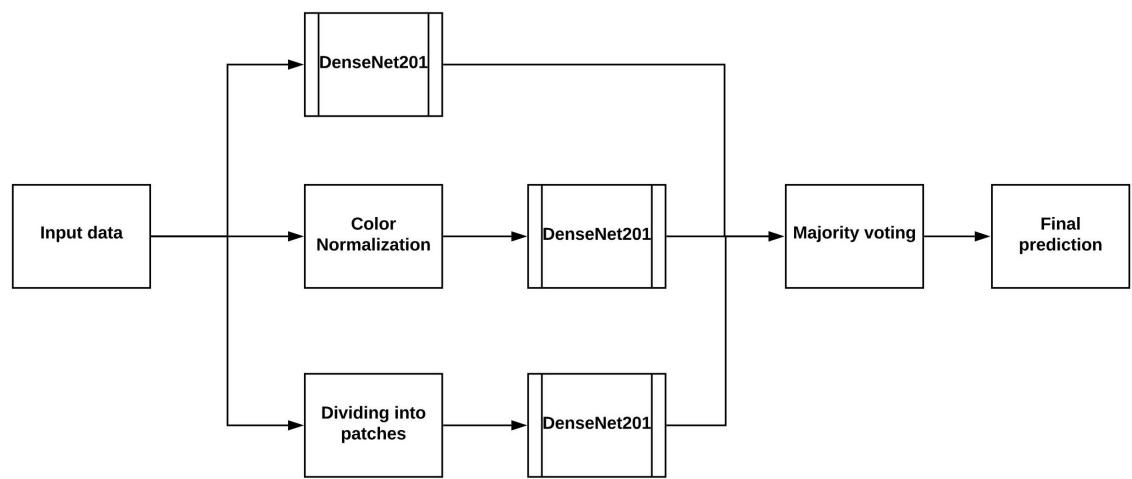


Figure 5.6: Majority Voting Architecture with 3 pre-trained Densenet-201 models.

# **Chapter 6**

## **Conclusion**

### **6.1 Summary**

We applied some preprocessing techniques like colour normalization, dividing the images into patches and resizing the patches. We have trained three cnn models with original dataset and got accuracy around 81%. We then trained Densenet201 cnn model with dataset that is colour normalized. We got accuracy around 84% for this model on test dataset. We then trained another Densenet201 cnn model with dataset where images are divided into patches and images are colour normalized. We got accuracy around 86% for this model on test dataset, Then we did majority voting of all the 3 models and we got accuracy of 88%.

### **6.2 Future work**

In future, we can apply data augmentation to the training dataset so that we can extend the dataset. If we apply data augmentation to our dataset, we will get around 1,00,000 images. As the dataset got extended, cnn model can now be trained on this dataset which will increase the accuracy of the model. We also need good amount of gpu's to train the model as data set is huge. In this project we trained the dataset on Densenet201 CNN model. We can also use other cnn architectures to train the dataset with different image sizes to find the output class and increase the accuracy.

# References

- [1] Aditya Golatkar, Deepak Anand, and Amit Sethi. Classification of Breast Cancer Histology using Deep Learning
- [2] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 770-778.
- [3] Huang, G., Liu, Z., van der Maaten, L., Weinberger, K.Q., 2017. Densely Connected Convolutional Networks, in: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE. pp. 2261–2269. doi:10.1109/CVPR.2017.243.
- [4] <https://iciar2018-challenge.grand-challenge.org/>
- [5] "Breast Cancer Classification from Histopathological Images with Inception Recurrent Residual Convolutional Neural Network", Alom, Md Zahangir and Yakopcic, Chris and Nasrin, Mst. Shamima and Taha, Tarek M. and Asari, Vijayan K., "Journal of Digital Imaging
- [6] Kaushiki Roy, Debapriya Banik, Debotosh Bhattacharjee, Mita Nasipuri, Patch-based system for Classification of Breast Histology images using deep learning, Computerized Medical Imaging and Graphics, Volume 71, 2019, Pages 90-103, ISSN 0895-6111
- [7] Computer-aided diagnosis of breast cancer based on fine needle biopsy microscopic images. Marek Kowal, , Pawel Filipczuk , Andrzej Obuchowicz , Jozef Korbicz , Roman Monczak
- [8] George, Y., M., Zayed, H., Roushdy, M., I., Elbagoury, B., M., 2014. Remote computer-aided breast cancer detection and diagno-

- sis system based on cytological images.IEEE Systems Journal, 8(3), pp.949–964.
- [9] Multiple Instance Learning for Histopathological Breast Cancer Images P J Sudharshana, Caroline Petitjean, Fabio Spanhol, Luís Oliveira, Laurent Heutte, Paul Honeine
  - [10] Grand challenge on breast cancer histology images.Guilherme Arestaa, , Teresa Araujo , Scotty Kwokc , Sai Saketh Chennamsetty
  - [11] Nadia Brancati, Maria Frucci, and Daniel Riccio. 2018. Multi-classification of breast cancer histology images by using a fine-tuning strategy. In International Conference Image Analysis and Recognition. Springer, 771–778.
  - [12] <https://towardsdatascience.com/simple-introduction-to-convolutional-neural-networks-cdf8d3077bac>