Detection of different types of cancer using deep learning

A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF THE DEGREE OF

MASTER OF TECHNOLOGY
IN
INFORMATION SYSTEMS

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CANDIDATE'S DECLARATION

I, B Vinod, Roll No. 2K20/ISY/05 student of M. Tech., Information Systems, hereby declare that the major project titled "Detection of different types of cancer using deep learning" which is submitted by me to the Department of Information Technology, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

Place: Delhi
Date: May 26, 2022

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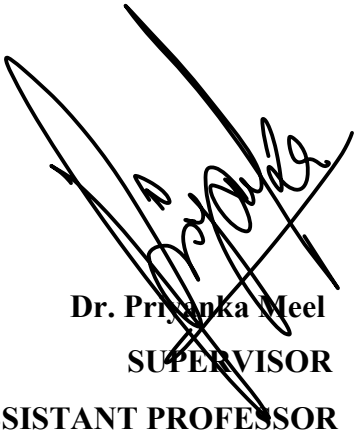
CERTIFICATE

I hereby certify that the major project titled "Detection of different types of cancer using deep learning" which is submitted by B Vinod, Roll No. 2K20/ISY/05 Information Technology, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degreeor Diploma to this University or elsewhere.



Place: Delhi
Date: May 26, 2022

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ABSTRACT

We provide an application of deep learning for cancer detection. We firstly provide what is a cancer, statistics of it and if not detected and diagnosed early can lead to death and then we proposed different models like CNN and how it can helps to detect or classify a cancer wheather a diagnosing person has cancer or not from a medical image(dataset). Image processing techniques have lately been popular in a number of medical sectors for image improvement at early diagnostic and treatment stages, especially in cancer tumours like lung cancer and breast cancer, where the time factor is crucial in detecting anomalies in target photographs. We have collected the dataset from kaggle which is a collection of dataset website and the dataset has been preprocessed to remove artifacts like blur, noise etc by various data cleaning technique and has been trained on a Deep learning models like basic CNN architecture, AlexNet, VGG16, ResNet-50, basic CNN architecture with dilation rate 2.0 and concatenation of two different architecture.

At last we evaluate and compare the model in terms of accuracy, precision, recall and F-Score using Confusion matrix.

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Chapter 1
INTRODUCTION

The simplest unit that makes up the human body is the cell and it grow and divide to make new cells and cells die when they get damaged or old and then new cells take their place.

Cancer takes place when cells grow continuously in uncontrolled manner without being stop and these are abnormal cells which may form a mass called tumor. If not detected and diagnosis early then it may spread to other parts of the body.

In the world, cancer is the second leading cause of death and the estimated number of patients with cancer in India is 13, 92, 179 for the year 2020 [1]. Cancer increases at the same rate in both male and female. Thus, both research and clinic doctors faced a big challenge of fighting against the cancers.

Early detection and diagnosis of a cancer can improve survival rate. Early cancer detection relies heavily on medical images. Medical imaging has been heavily used for early cancer detection, monitoring, and follow up after the treatment [2]. It can be tedious and time consuming when huge number of medical images interpreted manually and the chances of human mistake can also increase. Therefore, computer-aided diagnosis with medical image models and deep learning architecture are used to detect cancer with accuracy and efficiently.

Computer-Aided Diagnosis

Image classification by hand is a difficult and time-consuming operation. There is a substantial risk of human mistake in this manual activity. As a result, manual classification produces exceedingly poor results, increasing the burden of radiologists, who are in limited supply. And the expenses of medical treatment, which are crucial to imaging, are quickly rising. As a result, new diagnostic approaches are necessary. In diagnostic radiology and medical imaging, CAD is a key study issue. The CAD system assists medical physicians in more efficiently diagnosing illnesses while reducing examination time and expense and avoiding superfluous manual operations. CAD is still the most appropriate approach for initial cancer diagnosis, using medical images like magnetic resonance imaging (MRI), X-ray, computed tomography (CT), histopathological pictures, and mammography images. CAD serves as a useful link between the input pictures and the radiologist. The CAD aids doctors in detecting cancer earlier and more precisely. The computer-aided design (CAD) technology is more dependable and efficient. Specificity, sensitivity, and absolute detection rate are some of the criteria of this CAD system.

Feature Extraction

Feature extraction is the main step in detection of cancer in which we extract essential features of abnormal cells from medical images. For different image models and cancer types, different feature extraction techniques have been applied. Without a set of predefined features, no deep learning algorithm can work. The most fundamental requirement for using any image classification algorithm is the ability to define features. For example, in skin cancer detection we use wavelet transform and grey level Co-occurrence matrix as feature extractor to detect melanoma in skin cancer [3]. Deep learning benefits is that directly from raw images it can produce high level feature representation.

The below given histogram shows number of cancer patients in a particular year. As year passes the number of cancer patients increases in both males and females.

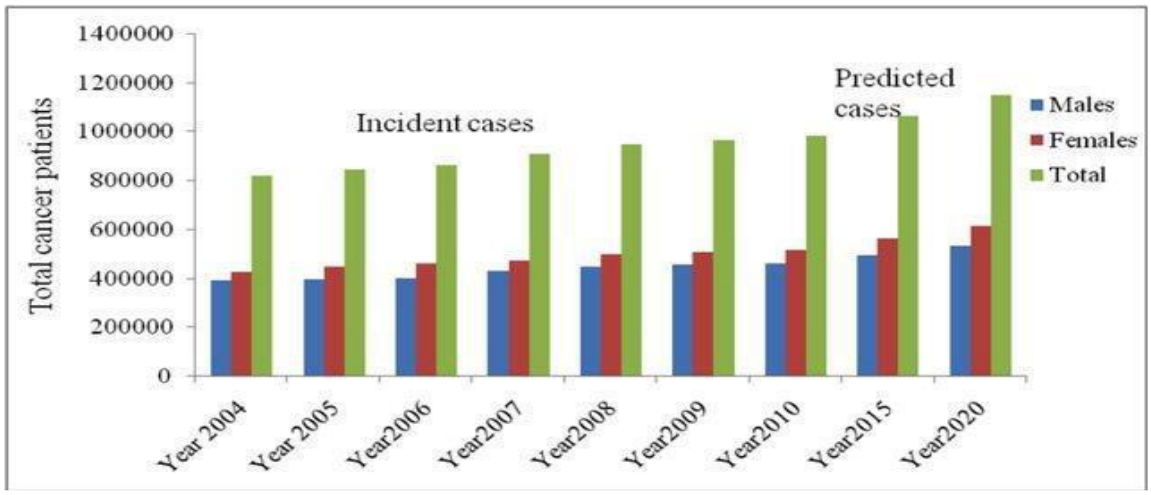


Figure 1: Number of cancer patients in a particular year [4].

The common 5 major cancers are breast, lung, skin, prostate and brain. Among all the cancers colorectal cancer (10%), prostate cancer (25%), lung cancer (15%) and skin melanoma (5%) are most common (by occurrence) cancers in males and colorectal cancer (10%), lung cancer (14%), breast cancer (26%) and skin melanoma (4%) in females [4].

The below given pie charts shows about the cancer occurrence in males and females and cancer mortality in males and females.

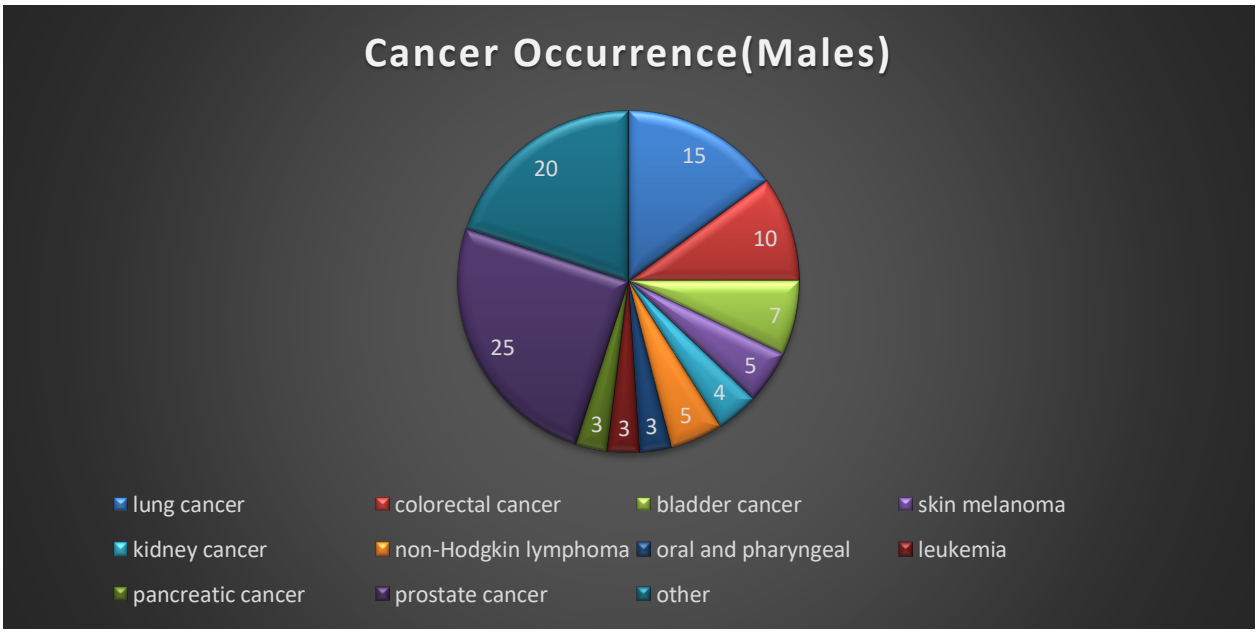


Figure 2: Cancer Occurrence in males

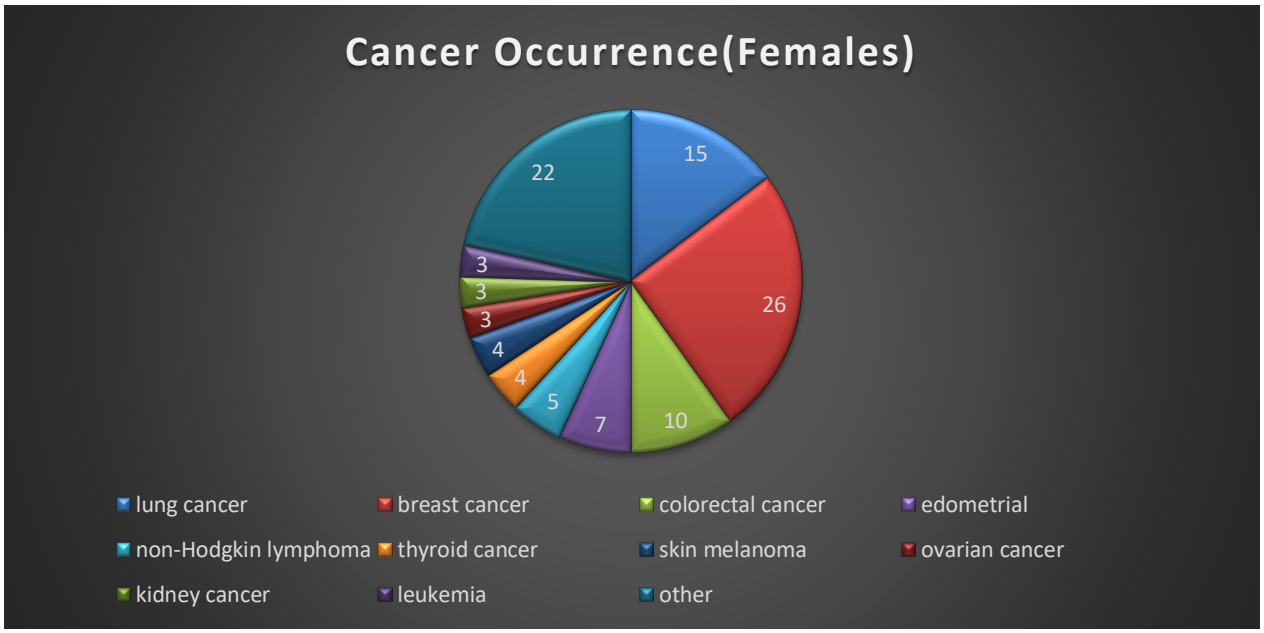


Figure 3: Cancer Occurrence in females

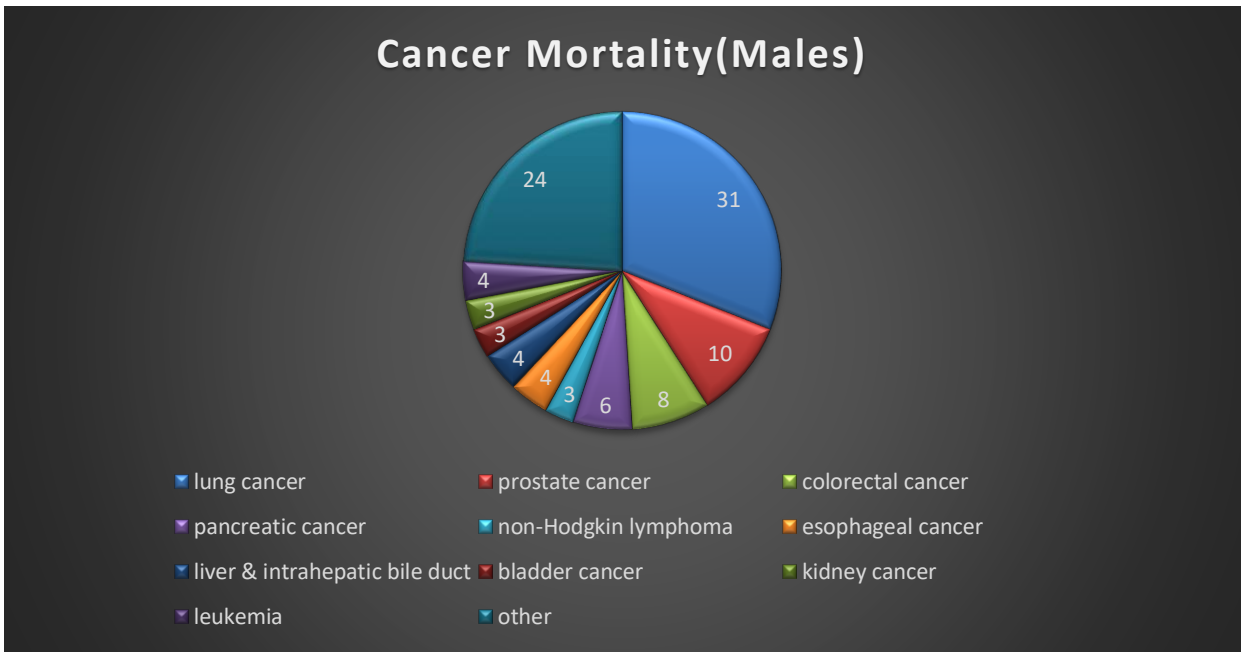


Figure 4: Cancer mortality in males

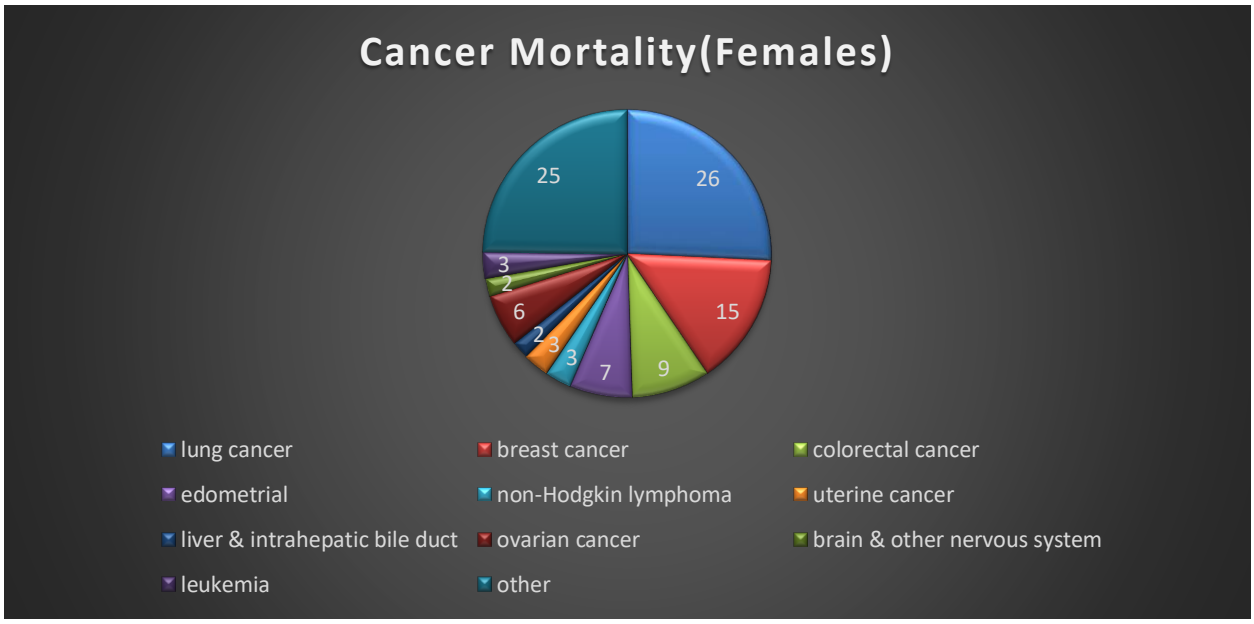


Figure 5: Cancer mortality in females

1.1 Review Methodology

Researchers use various intelligent methods to help segment and classify medical image data in order to recognize abnormalities (cancer) in different parts of the body. This form of research is limited to the use of most of these methods for medical image data classification and segmentation.

In this study the techniques and models that have been discussed are extracted from various reputed libraries such as the IEEE transaction, ResearchGate.

We have covered a discussion of study done in medical field for detection of different types of cancers. The above listed libraries have been studied and a review of all the models and techniques used by various researchers has been discussed.

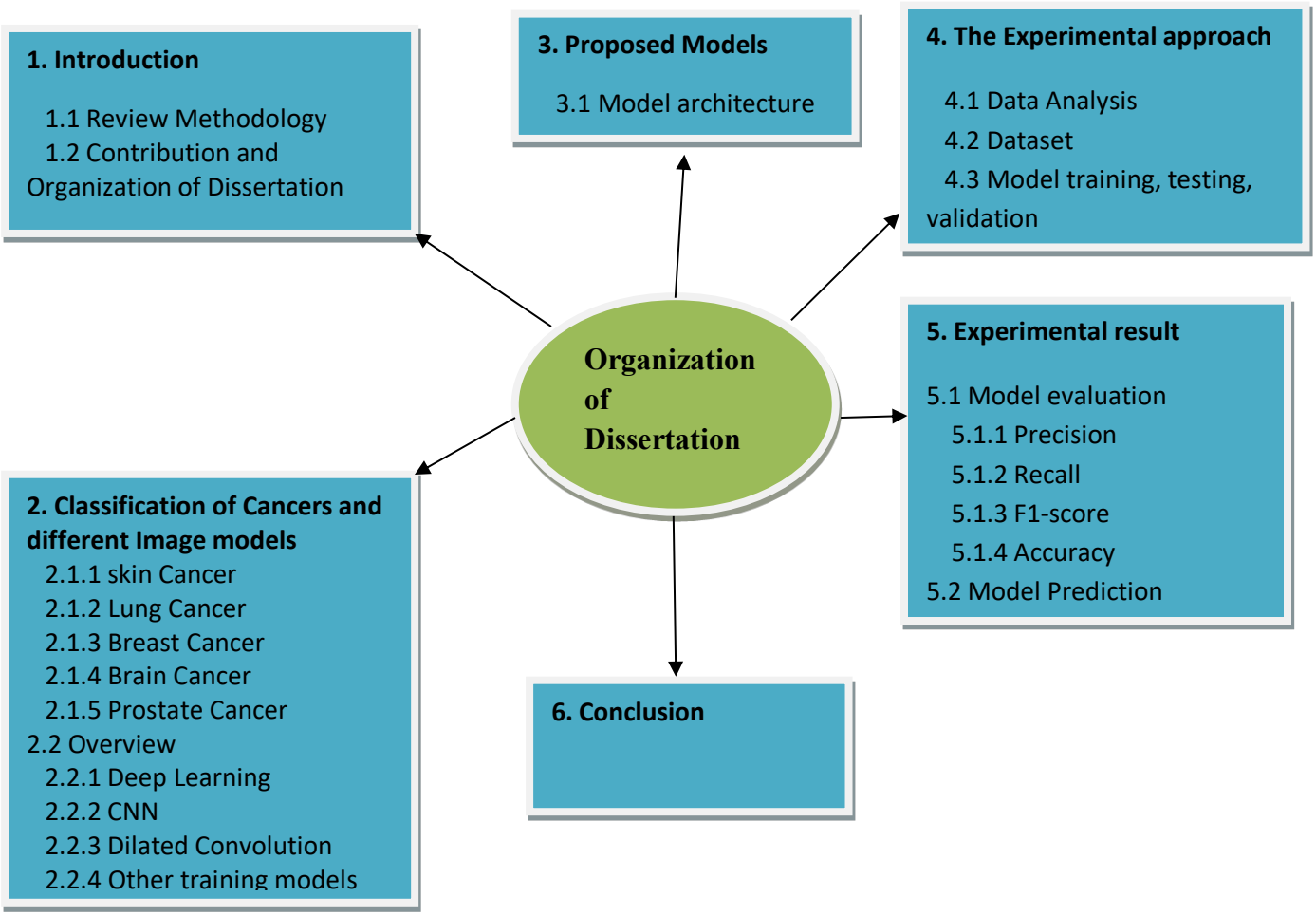
1.2 Contribution and Organization of Dissertation

In the 2nd chapter, we will discuss about classification of cancers and there different image models which used to detect cancer. The detailed deep neural network model content will be discussed in 2nd chapter.
The proposed deep neural network model to detect cancer from histopathological images of breast is discussed in the third chapter.

The chapter 4 presents the outcomes of our approaches on a standards dataset and validates the outcomes by demonstrating the likelihood of a statement being true.

The model's experimental approach will be discussed in the chapter 5.

The chapter 6 of the thesis is aimed toward a conclusion, with additional future research directions.



Chapter 2
CLASSIFICATION OF CANCERS AND DIFFERENT IMAGE MODELS

2.1.1 Skin Cancer

There are 3 types of skin cancer:

- Basal Cell Carcinoma (BCC)
- Melanoma
- Squamous Cell Carcinoma (SCC)

Among these 3 the Melanoma is most dangerous skin cancer type. The survival rate is very less in Melanoma skin cancer. The below given figure (histogram) shows that there is increase in skin cancer victim year by year in India.

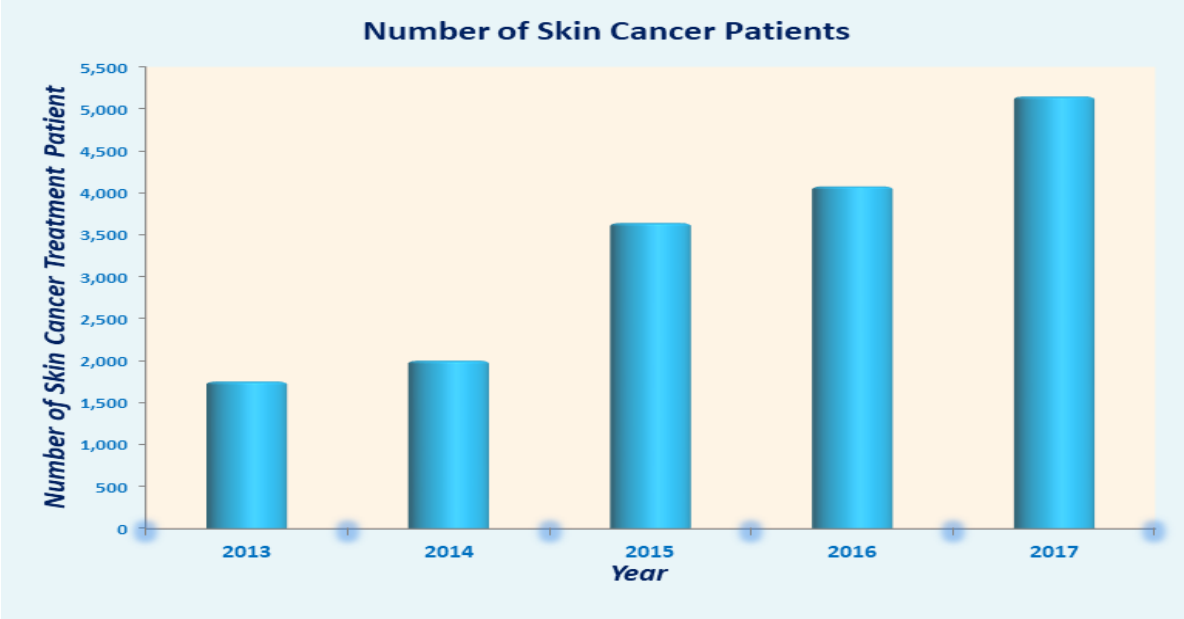


Figure 6: Number of skin cancer treatment patient in a particular year [6].

Statistics of India for skin cancer is 65%-75% of skin cancers are in whites and 20%-30% are in Asian Indians and most of them are Melanoma skin cancer patient [5].

Early detection and diagnosis of melanoma skin cancer can improve the survival rate. UK university found that 86% of melanoma is caused by ultraviolet radiation which coming out from sun rays and the person who uses SPF sunscreen before exposed to sunrays can reduce the risk of melanoma by 50% [6].

Due to survival rate is very less for melanoma skin cancer and early detection can save the life so we need skin cancer detection system with high accuracy.

For detecting a skin cancer we need an image of that cancer which is of two types:

I. Dermoscopy:
- It is a type of image which is captured by expert dermetalogist in pathological center with high zoom in region of interest to detect skin cancer is there or not.
- It require a patient to go pathological center and consult to dermetalogist.
- It is mainly suitable for diagnosis of skin cancer.
- It require a specialized device to capture image which is present in pathological center.

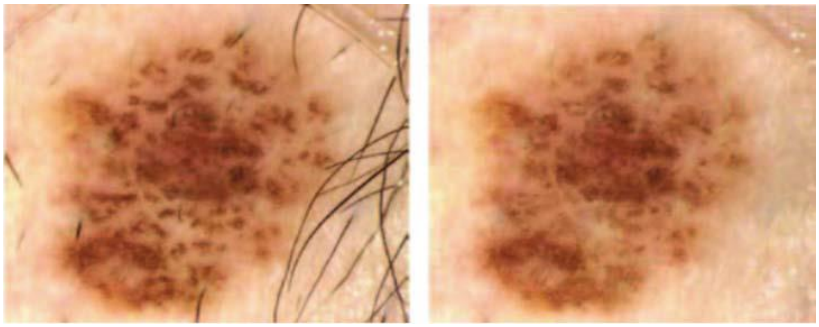


Figure 7: Dermascopy image before and after hair removal using filter [6].

II. Digital Image:

- It is a type of image which is captured by any digital image capturing device.
- It require a computer software which can be used by patient in home to detect skin cancer.
- It may not require to consult dermetalogist.

Images for detection of skin cancer are not directly feed into the classification algorithm to categorized. Before using any classification model we need to clear some artifacts like hair, noise in images so that the image become suitable for classification.
We use different digital image processing method to clear some artifacts and to make it suitable for classification. The given below figure contain steps to remove artifacts.

1. **Image Acquisition:**
   Capturing a required image from any suitable image capturing device or machine. Like for x-ray image we use camera which is sensitive to Xrays.
   The CT images having low noise when compared to any other images like MRI image.
   The benefits of the computer tomography image having low noise and better clarity.

2. **Image Preprocessing:**
   To improve the image by removing any artifacts like noise, air bubbles or blurring using some Digital image processing technique like histogram euilization, median filter.

3. **Image Segmentation:**
   Image segmentation is a partitioning of a image into various segments so that unwanted region which do not contain any information are discarded and locate or highlight the boundaries of the object(edges,curves) in images. It is major step in detecting abnormal cancer cells shapes.

4. **Feature Extraction:**
   Extracting a tiny features from an image using filters and convolution operation.
   In medical image we extracting features like normal cell and abnormal cells.

5. **Image classification:**
   To categorized the image with some probabilities of different class.And all class probabilities suming up to 1

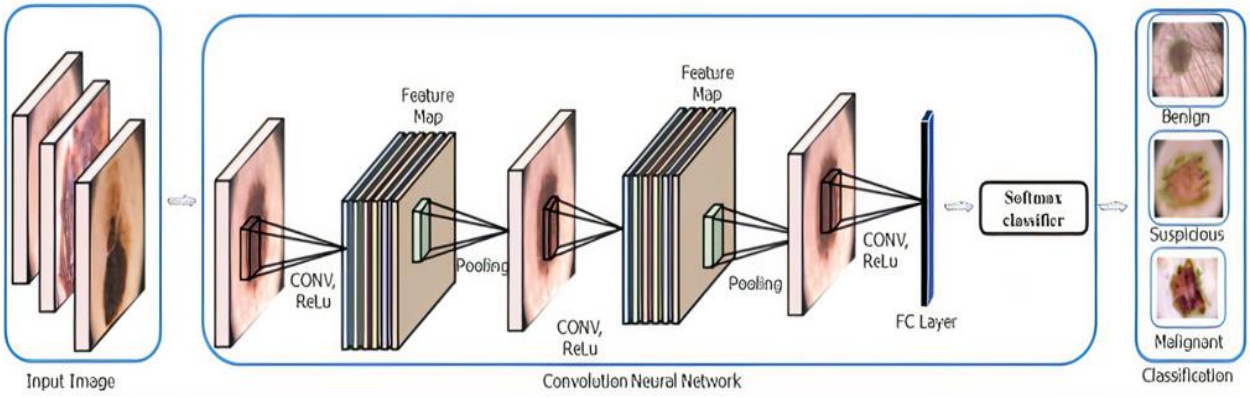


Figure 8: classification of skin cancer using CNN.

In [7], Enakshi jain, in the preprocessing phase uses median filter to reduce noise and remove hairs uses dull razor software which finds location of hair and replace hair by near-by pixels.
And contrast enhancement technique i.e. histogram equilization is used to focus on the region of interest clearly. Histogram equalization distribute the pixels value uniformly to get the better image visualization.
In [8], Esteva utilised a large dataset (129,450 clinical pictures) to examine pre-trained CNNs for skin cancer classification.

Refrences	Application	Image model	Deep learning model or Merits	Dataset
Enakshi jain [7]	Skin cancer classification	Dermoscopy	SVM and Adaboost	Unpublished dataset
Esteva [8]	Skin cancer classification	Dermoscopy	CNN	Open-access online dataset
A.Masood [9]	Skin lesion classification	Dermoscopy	DBNN and self advised SVM	ISIC[10]

Table 1. Papers summary on skin cancer detection

2.1.2 Lung Cancer

The lung cancer occur in 70% of the people above 65 years and less than 3% of the people which is below 45 years. Among all the new cancer cases in a particular year the lung cancer makes 6.9% and among all the death due to cancer, the death due to lung cancer makes 9.3% in both males and females [17]. The main cause of the lung cancer is smoking, tobacco and polluted air. Early detection or screening by computed tomography (CT) can reduce a lung cancer mortality rate by 15% - 20% but with a 96% of false positive rate.

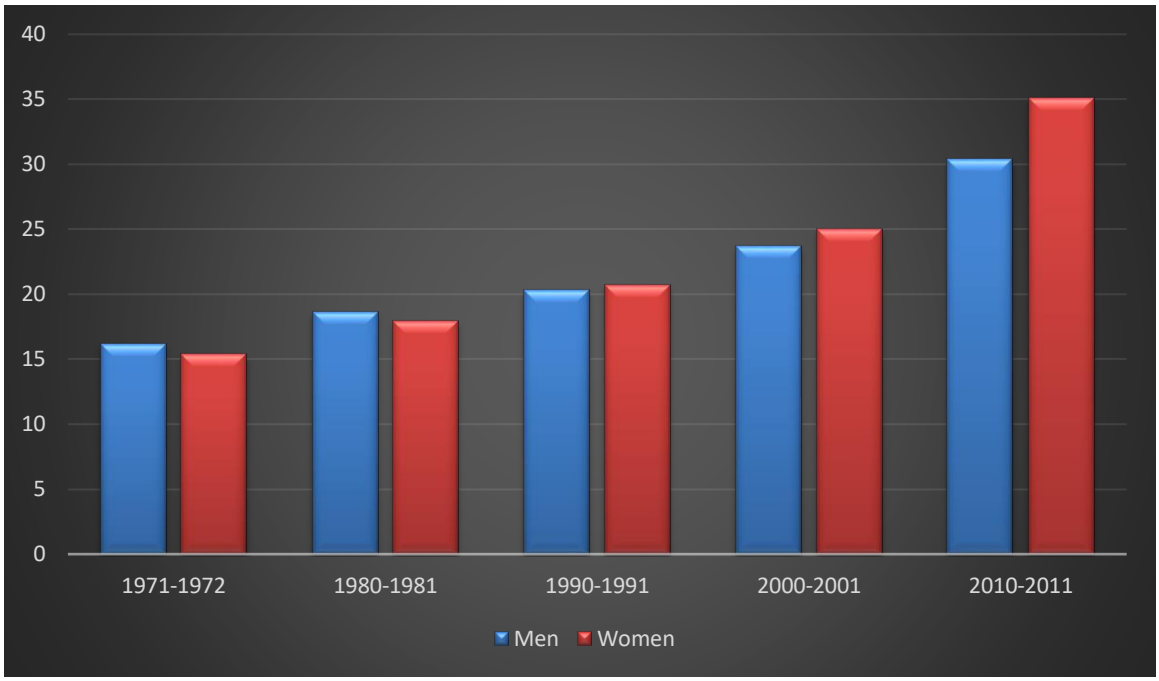


Figure 9: Period of Diagnosis (x-axis) and Net survival rate (%)(y-axis)

The Computed Tomography (CT) is image model used for detecting nodules in lungs. Detecting a nodule in lungs is not an easy task because nodule comes with variety of shapes, textures, types and size so extracting nodules feature is difficult and require many heuristic steps.
To increase accuracy of detection of nodules require image preprocessing, image segmentation before extracting features from CT and to increase training set or if number of nodules is less than the number of non nodules so to increase number of nodules set we apply data augmentation (scale, shift, zoom in, zoom our, rotating etc) in CT. The aim of the screening is to detect cancer in earlier stage so to diagnosis has been taken as per screening result and CT is important image for screening. CT scans provide greater details bones, internal organs and soft tissue compared to traditional X-ray. So, CT scans are preferable over X-ray for image
classification and to detect the nodule with very high sensitivity.

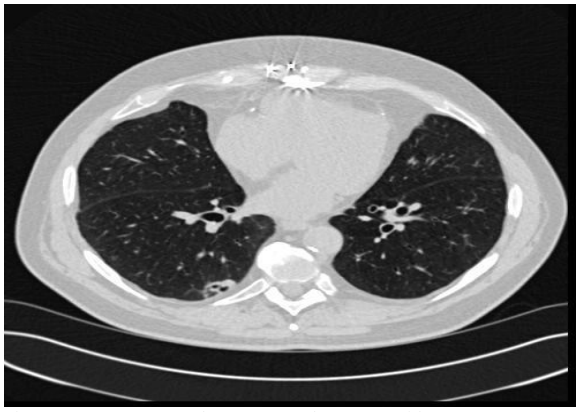


Figure 10: Computed Tomography scan of lungs [20]

As we know to detect pulmonary nodule from CT scan is difficult so to make somwhat easier we use **median intensity projection** algorithm in which the input is 3-D image means collection of CT images and make it one 2-D image by taking median pixel value from corresponding set of pixels of CT images. The given below is steps before feed into the classifier.

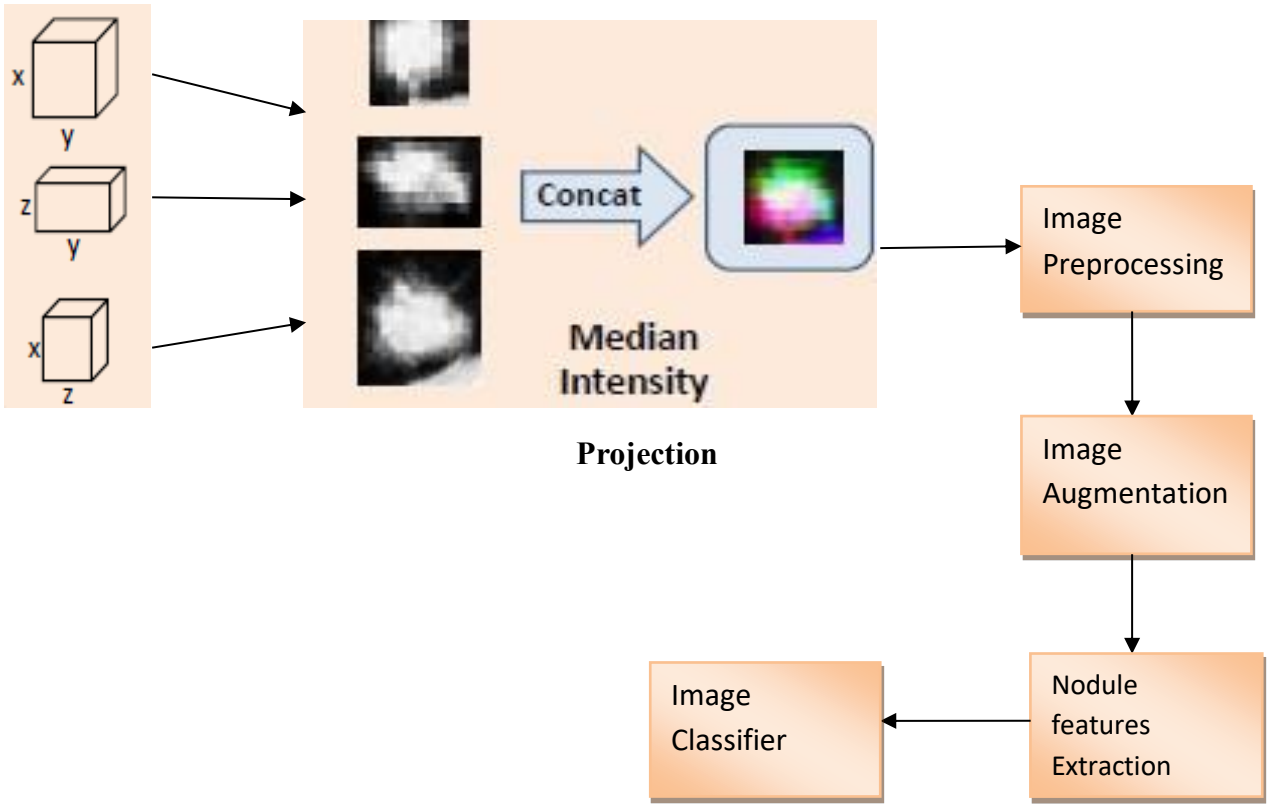


Figure 11: Steps involved before feed into the classifier.

1. Preprocessing

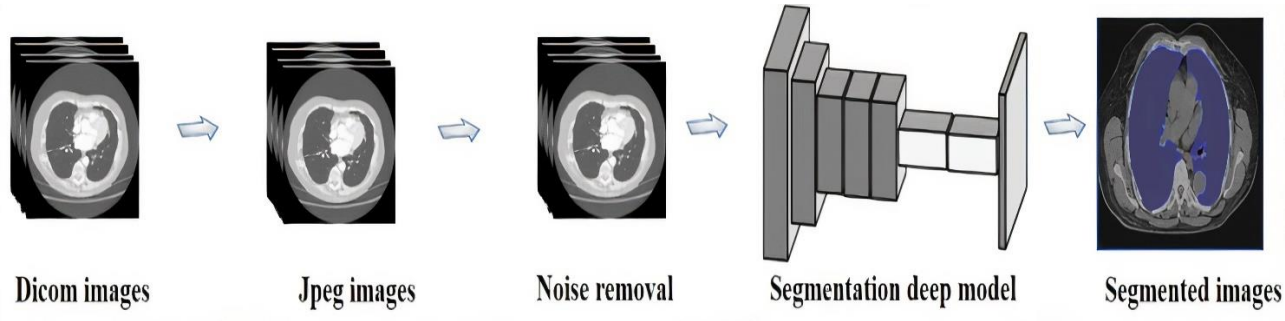


Figure 12: Preprocessing

2. Training Phase

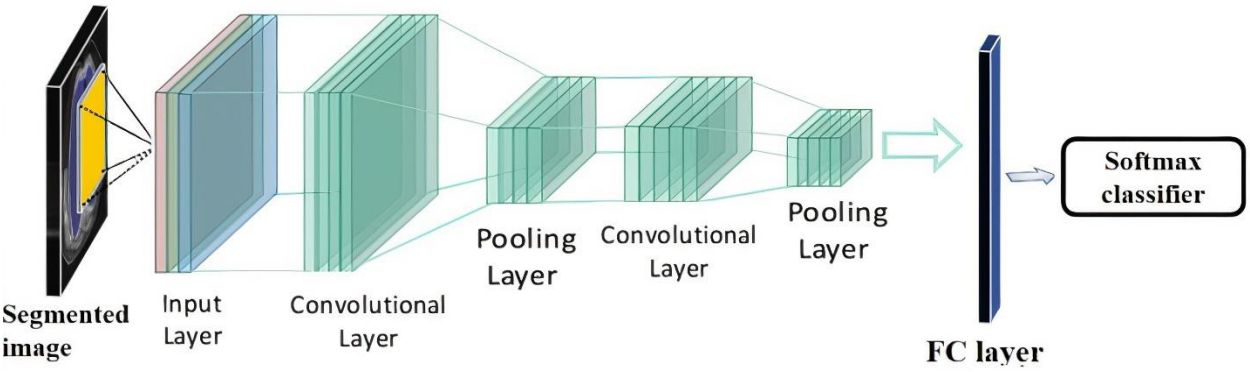


Figure 13: Training Phase

3. Testing Phase

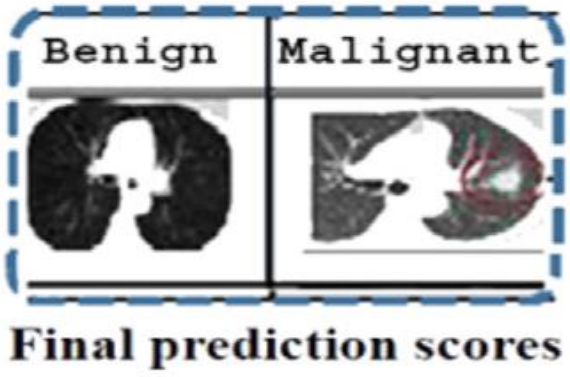


Figure 14: Testing Phase

In [12] Arnaud Arindra Adiyoso Setio, they have shown a CAD system for pulmonary nodule detection in CT scans based on multi-view convolution networks. They have shown that for nodule detection the ConvNets-CAD gives good results.
Deep learning algorithms were employed by K-LHua to classify pulmonary nodules in 2D CT scans [13]. In [14], Sarfaraz Hussein, perform end to end training using Multi view deep CNN which consist of 5 convolutional layer, 3 fully connected layer and final softmax layer. The first, third and fifth convolutional layer along with the maxpool layer which helps you with position invariant feature detection. A median intensity projection algorithm used in which the input is 3D image means collection of CT images and make it one 2D image by taking median pixel value from corresponding set of pixels of CT images. Q.Dou developed a three-dimensional convolution neural network (3D CNN) that learnt directly from 3D CT images rather than converting or producing 2D CT images to train a CNN model. [15].

Refrences	Application	Image model	Deep Learning Model	Dataset
K-L Hua [13]	Nodule Classification	Computed Tomography	DBN and CNN	LIDC-IDRI
Sarfaraz Hussein [14]	Nodule Classification	Computed Tomography	Deep Multiview CNN	LIDC-IDRI
Arnaud Arindra Adiyoso Setio [12]	Pulmonary Nodule Detection	Volumetric computed tomography	Multiview CNN	ANODE09[16]
Q.Dou [15]	Pulmonary Nodule Detection	Volumetric computed tomography	CNN	LIDC-IDRI

Table 2. Papers summary on Lung (Nodule) cancer detection

2.1.3 Breast cancer

Among all the cancer, the Breast Cancer in women is very common throughout worldwide. According to WHO (World Health Organization) 2.09 million cases are found and 6,27,000 deaths globally [8] and in her lifetime, one out of every eight women will develop breast cancer. Early detection of this cancer can improve the survival rate. Otherwise the cancer can spread to other parts of the body and then which can lead to death.
In most of the cases this cancer can occur in early thirties and peak at ages 40-50 years.

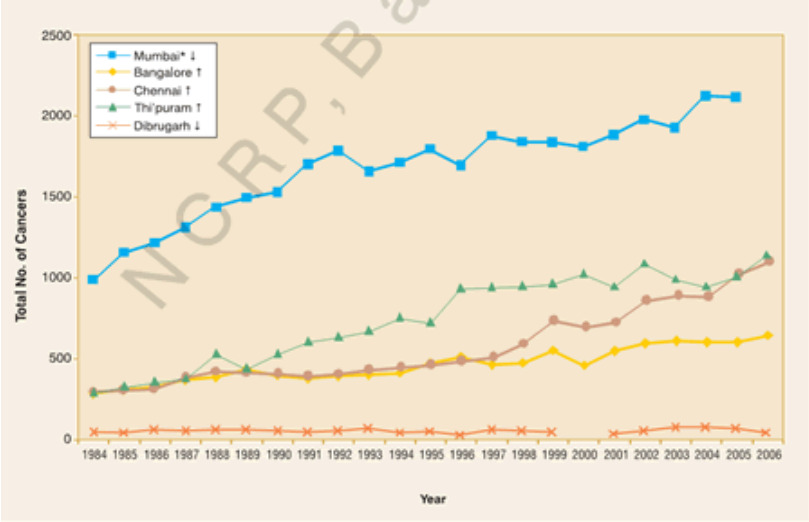


Figure 15: Total numbers of cases in different cities of India in particular Year [17]

There are 2 types of image model used in detection of Breast cancer

I. Histopathological images to detect mitosis in breast.

Mitosis is a cell which is of different shapes and low frequency and which led to breast cancer. Detection of mitosis in histopathological image is a challenging problem. And different feature extraction and classification has been used to recognize that pattern.

But the histopathological images are the mostly used images for breast cancer diagnosis.

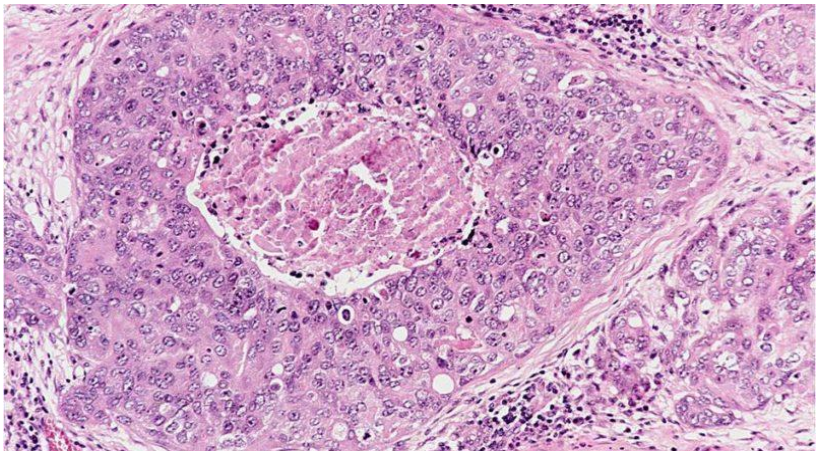


Figure 16: Sample histopathological image[18]

Before feed into any classification algorithm we have to make the histopathological image suitable for detecting the cellular structure for the feature extraction stage.

Some noises has to be remove while preserve image edges and determining the cell borders is very important which very helpful in feature extraction stage.

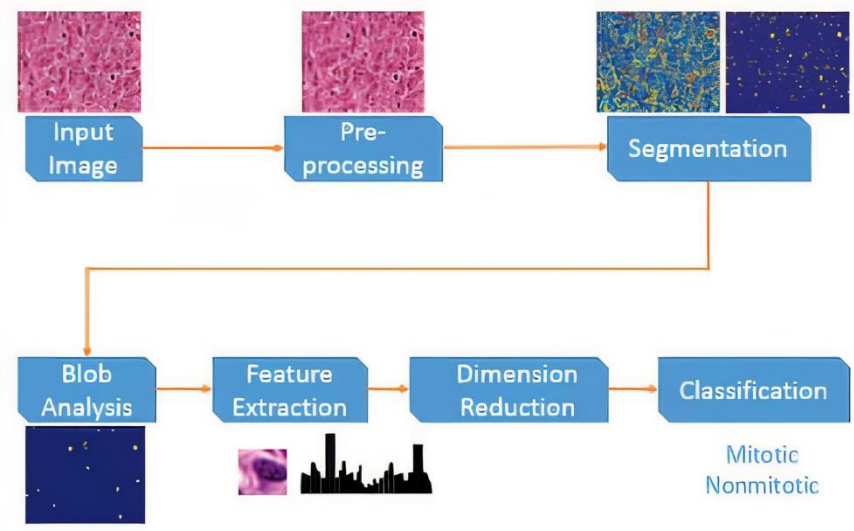


Figure 17: Image processing before feed into the classification model [19]

II. Mammogram:

This is another type of image model in which breast cancer is detected. Capturing a mammogram and detecting a mass in mammogram is not an easy task and it require specialist to do.

The first task is to improve mammogram image and make it suitable for classification using digital image processing methods. And this task contains reducing noise using filters and highlight the internal structure of the breast and focusing on the region of interest using image segmentation so that image become ready for classification and feature extraction.

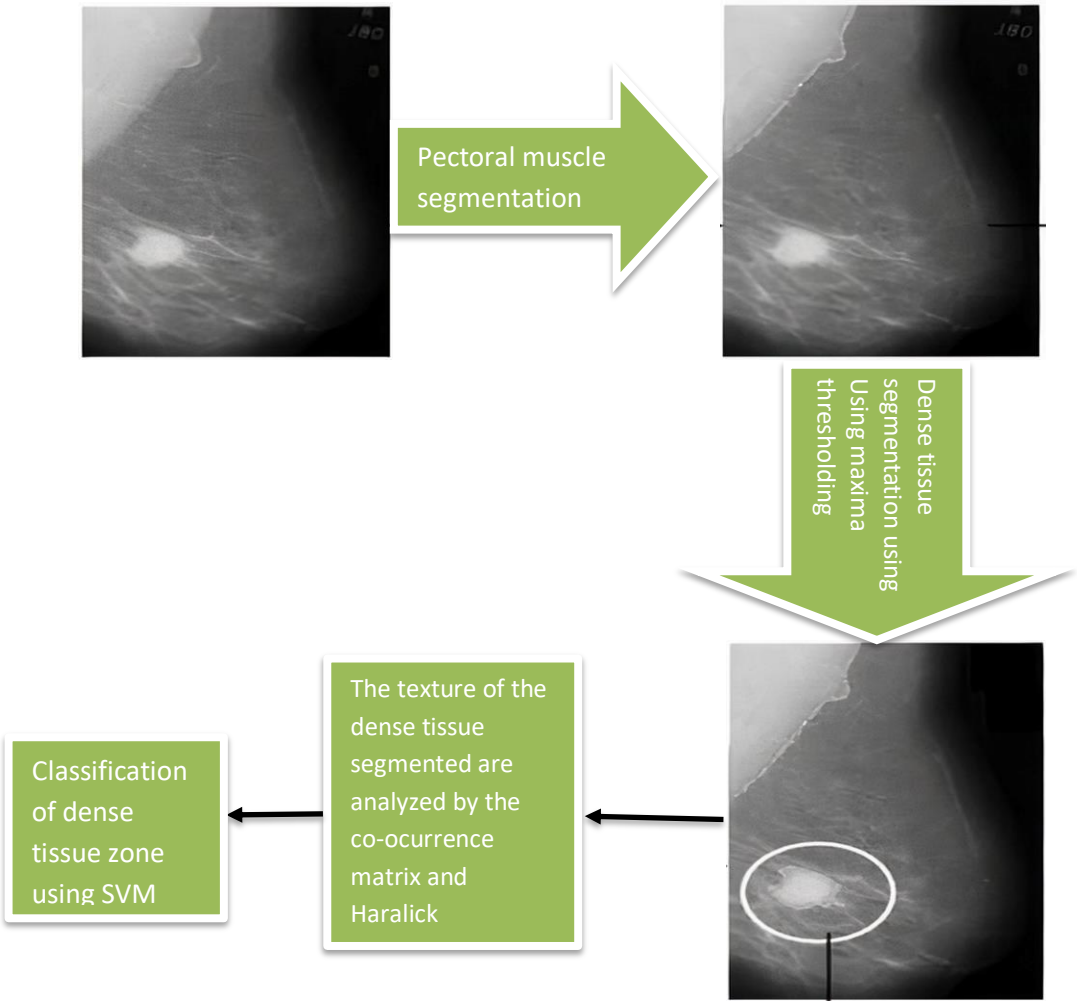


Figure 18: Mammogram before and after applying some image processing method [11]

In past years, many papers have been published about deep learning application in detecting the breast cancer. In [21], Albayrak developed a feature extraction algorithm focused on deep learning to detect mitosis in histopathological images of the breast. In [22], AlexNet was used by Spanhol to establish a CNN model to distinguish benign or malignant tumours from histopathological breast images. In [23] Itsara Wichakam, uses data preprocessing to remove

noise and make it suitable for feature extraction and uses ConvNets and for classification uses SVM algorithm. The input layer, output layer, and additional hidden layers such as transforming and pooling are all completely linked layers in the Convolutionary Neural Network design. Abdel-Zaher and Eldeib[20] proposed a CNN-based technique for identifying breast carcinoma via an unmonitored pathway network of deep faith values followed by a backward propagation route.

Refrences	Application	Image model	Deep learning model	Dataset
Spanhol et al.[30]	Breast cancer classification	Histopathology	CNN	BreaKHis[31]
Wichakam et al. [32]	Mass detection	Mammographic	CNN	INbreast [33]
Chen et al. [34]	Mitosis detection	Histopathology	Hybrid (CNN+FCN)	MITOSATYPIA-12, MITOSATYPIA-14 [35]
Suzuki et al. [36]	Mass detection	Mammographic	CNN	DDSM [37]

Table 3: Papers summary on Breast cancer detection

2.1.4 Brain Cancer

Brain cancer is one of the most dangerous type of cancer and if not detected early and treated then it can lead to death. Generaly brain tumors are abnormal cells which grow in the brain in a uncontrolled manner. Brain tumors ranked 10^{th} in very common type of tumors among the people of India in 2018 and according to International association of cancer registries (IARC) there are 28,000 cases reported each year in India for Brain tumor and more than 24,000 people are died due to brain tumor annually [14]. Early detection of brain tumor is necessary to improve survival rate.

There are two types of brain tumor – Benign which are not cancerous and which cannot be spread to other parts of the body and another one is Malignant which are cancerous and which can be spread to others parts of the body.

Comparison to any other cancer, brain cancer has most mortality rate among children and adults under the age of 40. The below given figure is about number of brain tumor surgery in a given year.

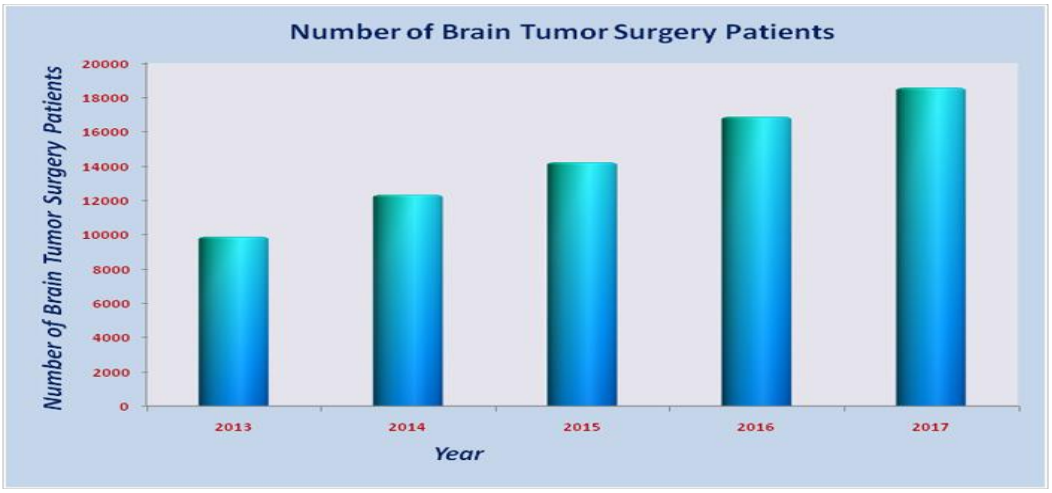


Figure 19: Number of brain tumor surgery in a given year in India [25].

Gliomas is the most aggressive and most common type of brain cancer which develop inside and center part of the brain and due to this reason gliomas is difficult to localize.
The survival rate of gliomas is less as compared to any other brain tumor with a life expectancy of at most 2 years.

MRI (Magnetic Resonance Image) is the image model which is used to detect brain tumor. The segmentation of gliomas from MRI is important for detecting and for diagnosis of brain tumor. But the segmentation of image to detect abnormalities when compared to healthy tissue is not an easy task since the size, shape, texture, locations and borders are often fuzzy or variable.
Before fed into any classifier it is required to remove artifacts from MRI using image preprocessing and image segmentation for highlight the abnormal cell (tumor) among all normal tissue. The given below is an Magnetic Resonance Image of brain.

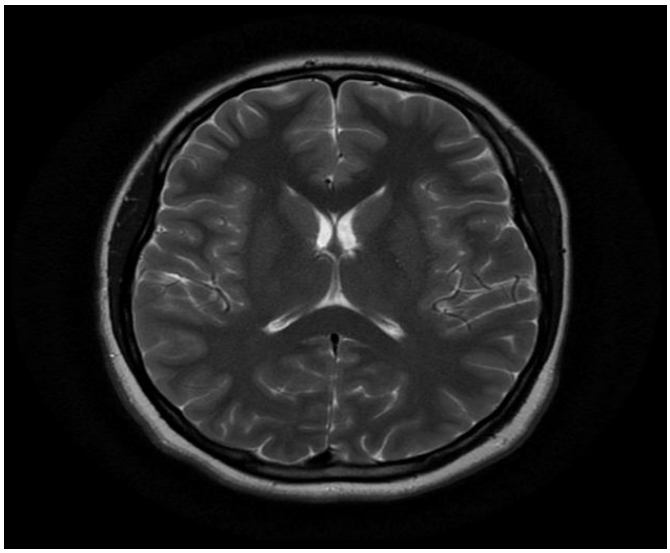


Figure 20: Magnetic Resonance Image of brain [26].

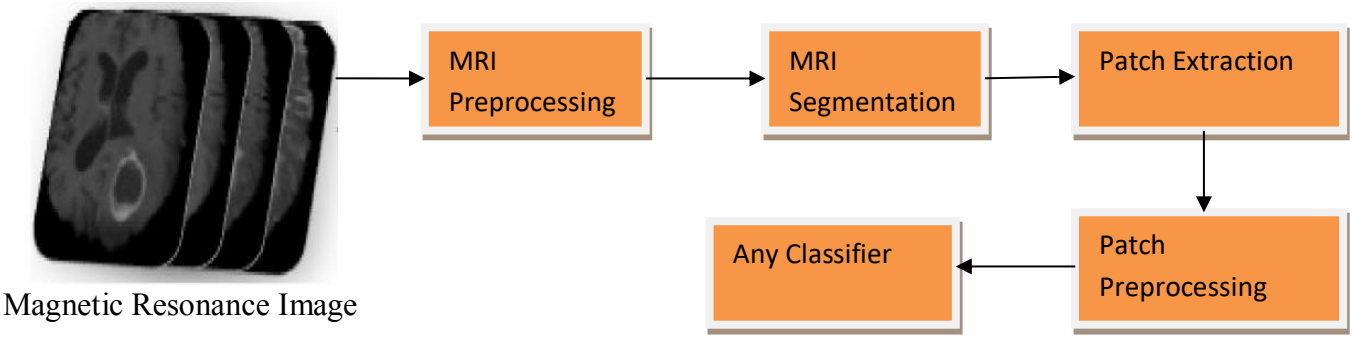


Figure 21: steps before feed into any classifier.

In this, two convolutional neural networks, Based on 2D slice images and 3D images, a 2D CNN and a 3D CNN were separately trained and then the final prediction result was created by integrating outputs from the 2D and 3D CNNs. This approach was better than any previous 2D and 3D scale-invariant feature transformation (SIFT) and KAZE function algorithms.[27]
Multi-layer feed forward neural network algorithms using MRI images were proposed (Al-Naami, Mallouh, & Hafez) and obtained an 86.9% accuracy score.
A CNN based approach for automated MR image segmentation was proposed by Pereira [28].

Refrences	Application	Image Model	Deep Learning Model	Dataset
Pereira et al. [38]	Brain tumor segmentation	Magnetic resonance image	CNN	BRATS [39]
Zhao et al. [40]	Brain tumor segmentation	Magnetic resonance image	CNN	BRATS
Ahmed et al. [41]	Brain tumor classification	Magnetic resonance image	CNN	Unpublished dataset
Liu et al. [42]	Feature representation learning of brain tumor	Magnetic resonance image	CNN	Unpublished dataset

Table 4: Papers summary on Brain cancer detection

2.2 Overview

This section will describe the planned approach for doing histopathological image detection for cancer, which is implemented on a deep convolutional neural network model. In which we designed a deep convolutional neural network as from scratch.

2.2.1 Deep learning

Deep learning is subset of ML that contains artificial neural network, that are algorithms inspired by biological and function of the human brain.

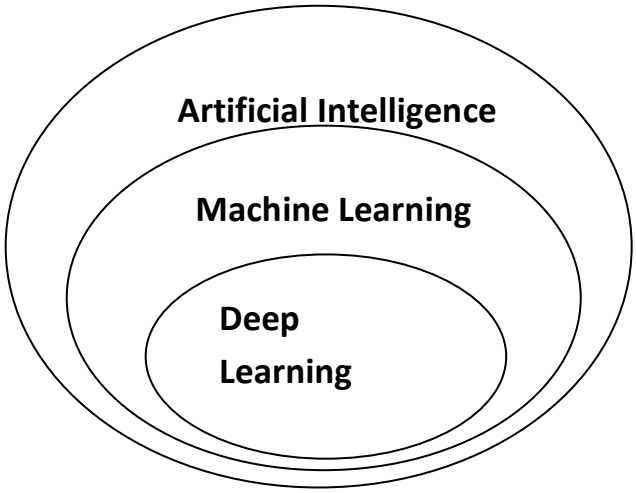


Figure 22: Machine learning, Deep learning and Artificial Intelligence

Deep Neural Networks evaluate data in/ an structured manner to reach comparable results as humans. Deep learning achieves this by putting a algorithms to work with multiple layers known as neural networks.

We may use neural networks to accomplish a wide range of activities, like as, classification, regression and clustering. Based on the patterns between the samples, we may utilize neural networks to categorize / classify unlabeled data. In the classification step, we can train the DNN model on a labeled dataset for categorize the data in this dataset among various categories.

2.2.2 CNN

Convolution neural network is a one type deep learning model. This neural network is feed forward neural network where signal flow from output of one neuron to input of next layer neuron means there is no feedback.

A CNN is a technique that takes an image is processed and assigns weights to the features in the image so that they can be discriminated. Compared to other classification techniques, CNNs don't require that much preprocessing. The filters can be learned by the convolutions themselves. The architecture of CNN is the structure of neurons as a source of inspiration in the human brain.
In an image, it can capture many temporal and spatial connections. CNNs are capable of performing complex tasks using multi-modal data such as images, text, audio, and video. LeNet, AlexNet, VGGNet, GoogLeNet, ResNet, and ZFNet are examples of ConvNet designs.
CNN uses multiplication of an image matrix with a for extracting features and pre-determined characteristics from it. We use a channel to filter the image and get only the predominant important features. The images are matrices of pixel values, and the filters are commonly 3x3 or 5x5. The

filter is moved across the image with a specified stride, and the values are multiplied and added to provide a matrix output that is easier to understand.

$$F(x) = f_n(f_{n-1}(\dots f_i(x))$$

Where 'n' is number of hidden layer and 'fi' is function used in corresponding layer.
In a CNN model there are basically 5 layers.

- Convolution layer
- Activation function layer
- Pooling layer
- Fully connected dense layer
- Predication layer

1) Convolution layer

In convolution layer it uses filters size n*n and apply convolution operation all over the image using these filters and extract the tiny features of the image which we called feature map. For example: In nodule detection in lung cancer we use to detect edges, shapes, abnormal cells etc.

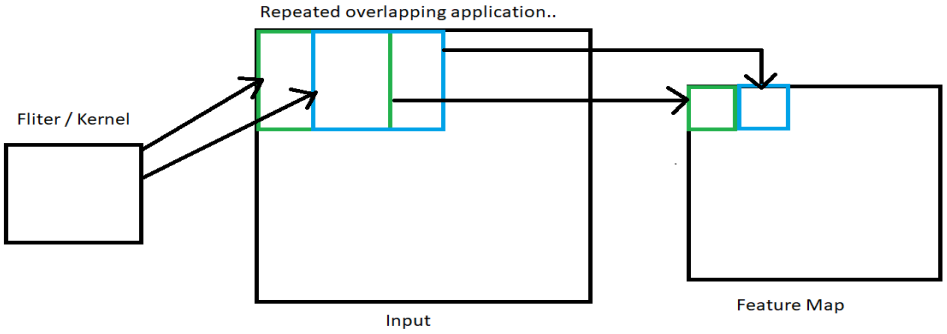


Figure 23: Applying filter in input image

2) Activation function layer

In this layer we use any non linear activation function to bring non-linearity in our model which speeds up training and faster to compute. It is used to learn and understand complex pattern in our data as well as to prevent the numbers from aggregating to zero. Mostly we use RELU (rectified linear units) as a activation function which can be expressed as

$$\boldsymbol{f(x) = \max(0, x)}$$

There can be other activation function too like sigmoid, tan h and exponential linear units (ELU) etc.

- **Linear activation function**

The equation for a linear function is y= mx, which is the same as the equation for a straight line.

Equation : f(x)=x

Range: -∞ to ∞

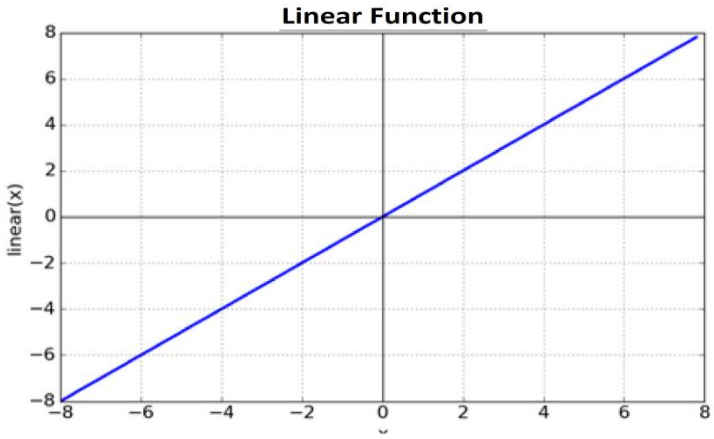


Figure 24: Linear Activation function

- **Sigmoid Function:**

The sigmoid or sigmoid activation function's curve resembles an 'S' shaped curve. Between zero and one is the range of the logistic activation function. Because value of the sigmoid function is limited between zero and one, the outcome is likely to be one if the value is greater than 0.5 & zero else.

Equation: f(x)= $\frac{1}{(1+e^{-x})}$

Range: 0 to 1

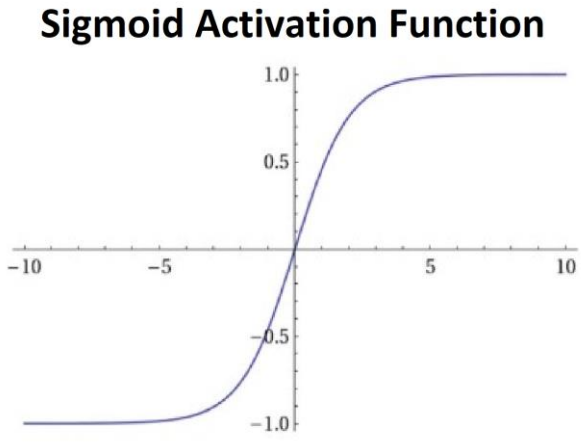


Figure 25: Sigmoid Activation Function

- **Tanh activation function**

Tanh is a hyperbolic tangent function, similar to the logistic sigmoid. The curves of the Tanh and sigmoid activation functions are quite similar, as illustrated in figure 2.13, however Tanh is preferable since the whole function is zero centric.

Equation: $f(x)=\tanh(x)=\frac{2}{(1+e^{-2x})}-1$

Range: -1 to 1

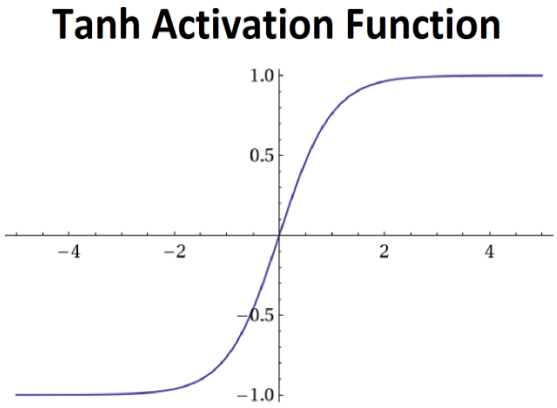


Figure 26: Tanh Activation Function

- **ReLU activation function**

It's most often used activation technique in hidden layers of a deep neural networks. It's the most used activation method in DNN hidden layers. Because the ReLU function is non-linear, we may quickly back transmit errors and trigger multiple layers of neurons. ReLU is less expensive than hyperbolic tangent and sigmoid because it uses fewer complex computations. Because just a few perceptrons are engaged at any given moment, the cnn is sparse and quick to process.

Equation: f(x) = max (0, x)

Range: [0 to ∞)

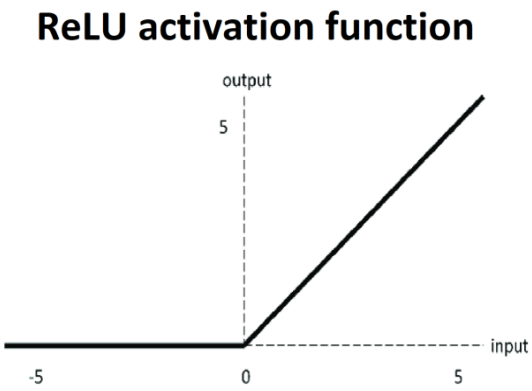


Figure 27: ReLU activation function

- **Softmax activation function**

The softmax function is a function that deals with classification tasks at fully connected layer. When dealing with many classes, this is commonly employed. The softmax function has range from zero to one. The softmax function is best used at the output layer of the deep neural network, where we want to use probability to characterize the classification from each input.

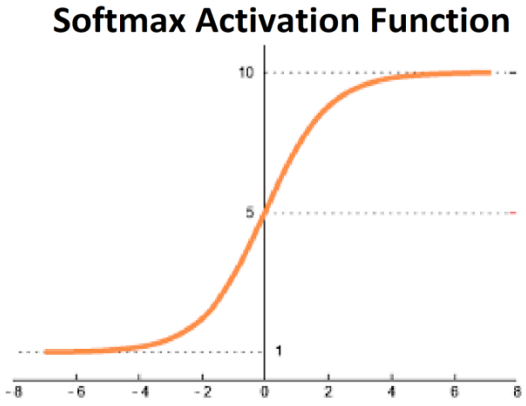


Figure 28: Softmax Activation Function

3) Pooling layer

This layer actually used to reduce the size or reduce the dimension of image (feature representation). By experiments it was found that Max pooling is used mostly. In Max pooling we use a window of size m*m and take maximum pixel value among all the pixel values in window of feature map and slides to stride of 'k' and by doing this it cover the whole feature map.

There are several forms of pooling, such as maximum pooling, minimum pooling, average pooling, and so on.

- **Max Pooling:**

A method of determining the highest weight of sectors by pooling them together of a feature map and uses it to construct a down sampled (pooled) map of features is called as Max-Pooling. After a convolutional layer, it's typically used. By employing pooling layers, the size of the convolutional matrix are reduced. As a result, the number of learnable parameters is reduced, as is the network's processing complexity.

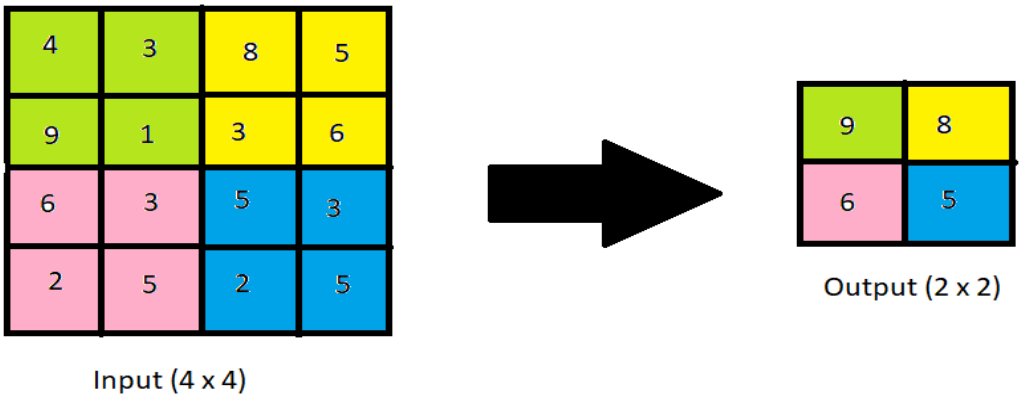


Figure 29: Applying 2x2 max-pooling on input

- **Average Pooling:**

The average of the values accessible in the region of the feature space covered by the kernel is used in average pooling. The pooling layer creates a connection between the convolutional and fully -connected layers in general.

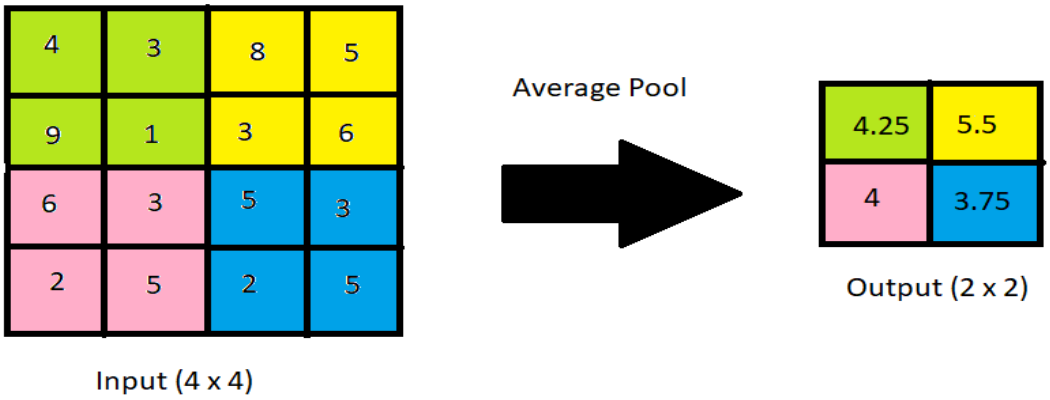


Figure 30: Applying 2x2 Average pooling on input

4) Fully connected dense layer

This is the last layer, where the categorization takes place. Here, we combine our filtered and shrunk images into a single list which is called vector.

In Fully connected dense layer each neuron is connected to every other neurons of next layer.

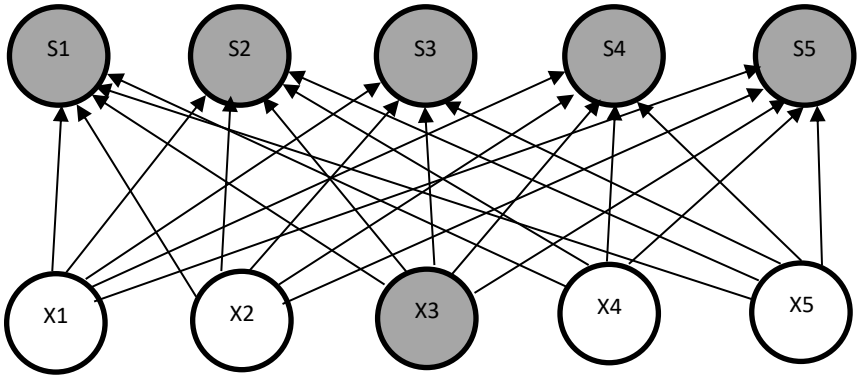


Figure 31: Fully connected dense layer

5) Predication layer

The predication layer is added to last layer of fully connected dense layer to compute probabilities of the different classes. Example: Softmax, SVM.

The below given figure shows convolution neural network architecture.

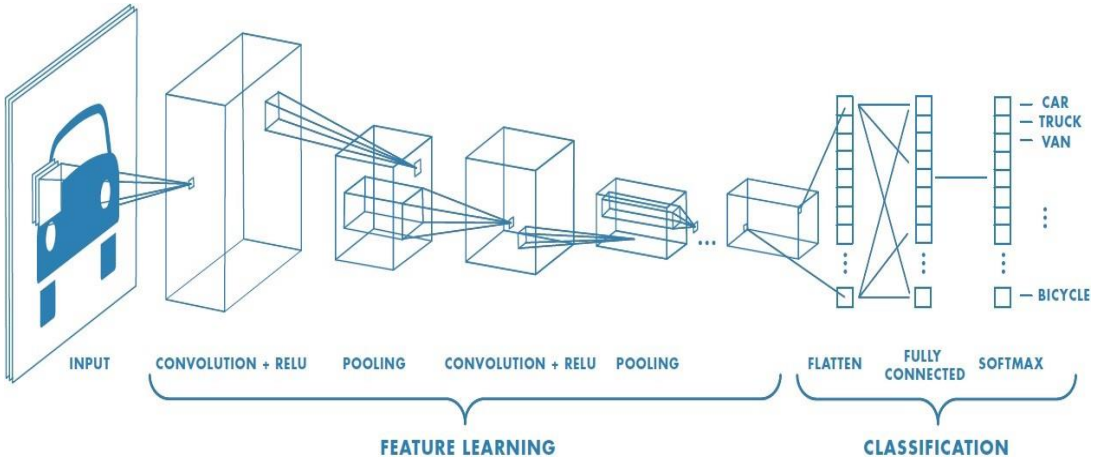


Figure 32: Neural network with many convolution layer [29].

6) Dropout Layer:

When a perceptrons/neurons in a neural network is turned off with a probability P during training, the term "dropout" is used. Assume a probability of P = 0.25, which means that throughout training, 25% of the neurons will be dropped. As a result, a quarter of the neurons with in neural network would not be examined, and the neural network will become easier. To avoid overfitting, we add a dropout layer in the CNN. Simple terms, throughout the training process, a certain number of neurons are discarded from the deep neural network in the dropout layer.

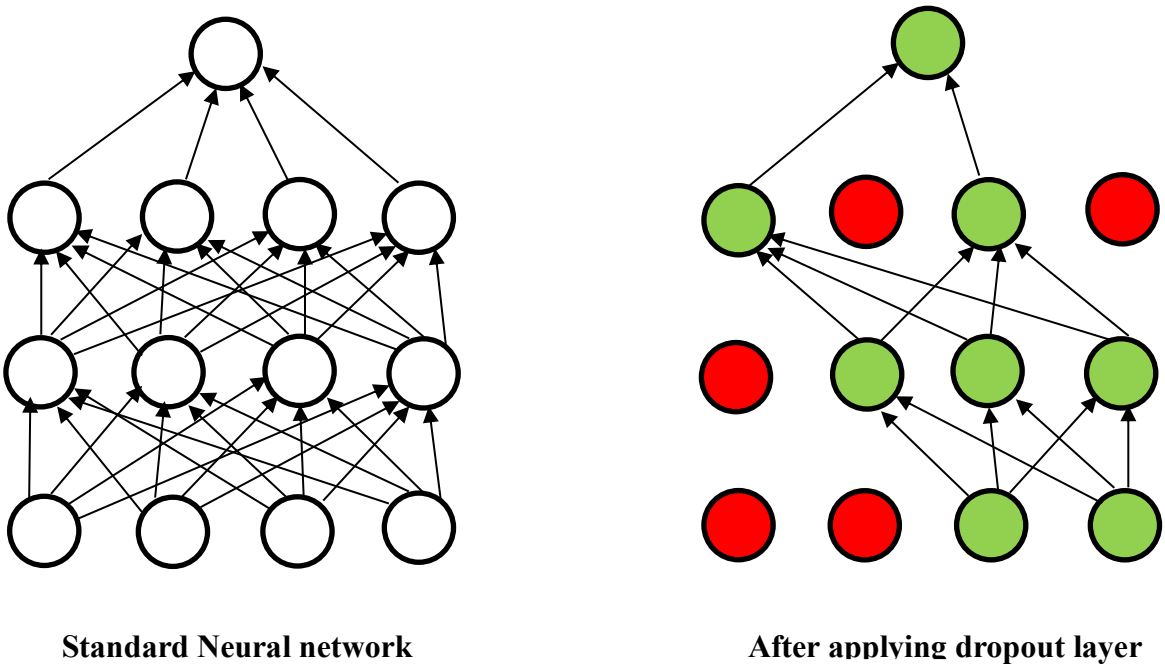


Figure 33: Dropout layer in the neural network

2.2.3 Dilated Convolution

It's a mechanism for expanding a kernel or filter by making holes in between the elements. In layman's words, that's the same as convolution, but now with pixel skipping to cover a broader area of the input. The 'dilation factor' argument specifies just how far the input is stretched. In other terms, the filter skips (dilation factor-1) pixels dependent on the value of dilation rate.
We can get additional information without increasing the number of filter parameters by employing this technique. Dilated convolution allows you to cover a larger region of the input images without pooling. The goal is to extract more details from the output after each convolution layer. At the same computing cost, this approach provides a larger field of vision. We calculate the value of a 'dilation factor' by evaluating how much knowledge is collected with each convolution at different 'dilation factor' values.

Dilated Convolution's Benefits:

- A more expansive receptive field is available.
- Effective in terms of computation.
- Memory usage is lower.
- There is no degradation in the produced image's resolution.
- The convolution's structure assists in keeping the information in order.

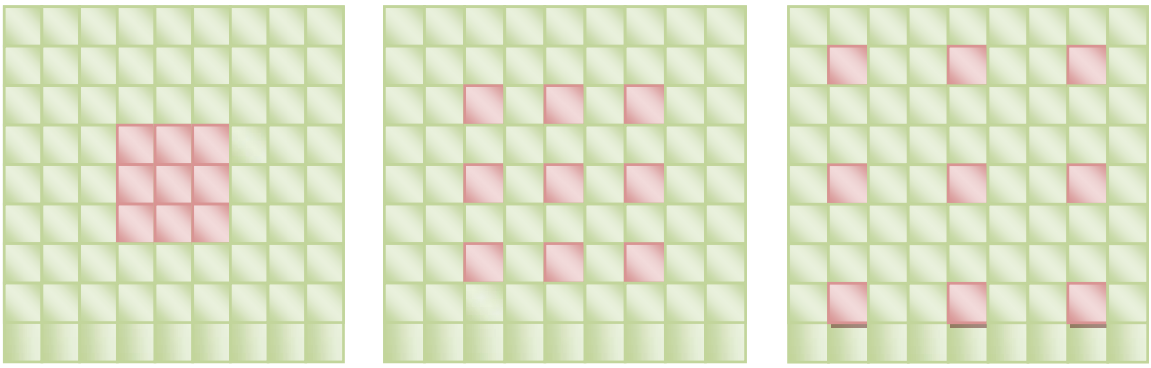


Figure 34: Dilated Convolution

2.2.4 Other training models

- **AlexNet**

AlexNet consists of five convolutional layers and three fully linked layers. To extract relevant functions from a picture, a number of convolutional kernels are used. There are frequently numerous kernels of identical length in a convolutional layer. In many circumstances, the kernel's dimensions are the same, and the depth is equal to the number of channels in the picture, depending on whether it's grayscale or RGB.

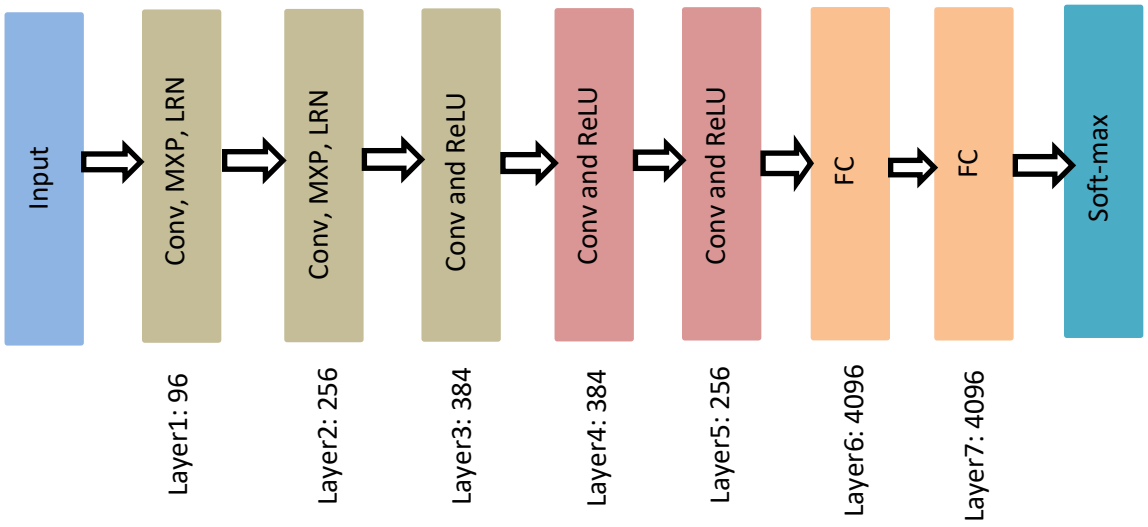


Figure 35: AlexNet Architecture

After the first two convolutional layers, there are max pooling layers. The three levels adjacent to it are linked in order. One overlapping max pooling layer exists in the fifth convolutional layer. Its output is sent into a series of two entirely linked layers. A SoftMax classifier with 1000 class labels is fed from the 2d completely linked layer. After all of the convolution and completely connected layers, ReLU nonlinearity is applied.

- **VGG16**

VGG16, a well-known deep learning model is chosen as a classifier, available in the TensorFlow library. This model has been used as a base for adding a new untrained head. The VGG16 is a Deep Neural Network architecture that is comprised of 2 convolutional filter layers and 1 pooling layer which is repeated twice. Then, 3 times, 4 convolutional filter layers and 1 pooling layer were applied. Lastly, 2 fully connected layers and then a softmax output.

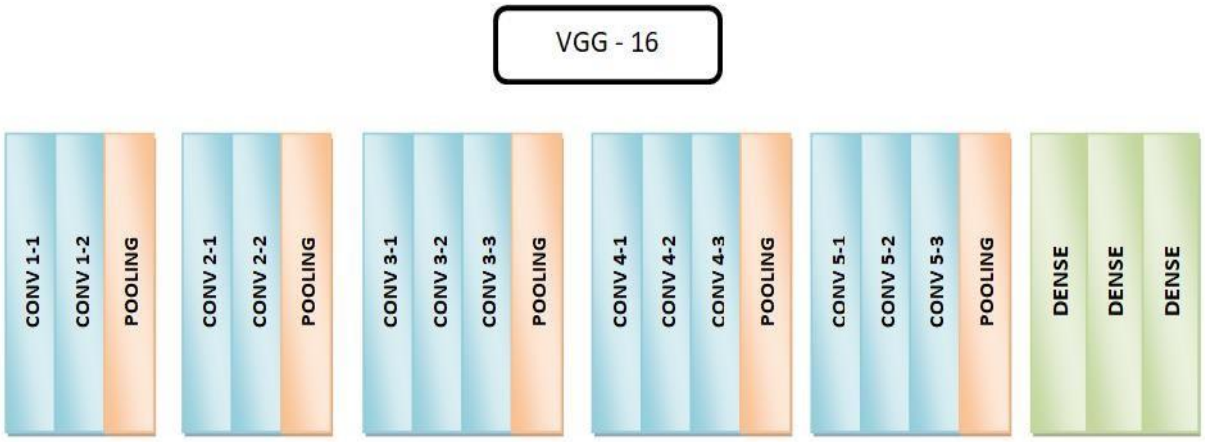


Figure 36: VGG16 architecture as base model

The final layers of the pretrained network are discarded and replaced with new layers to meet the new classification task. A 0.2 dropout layer, a flatten, and two fully linked networks of dimensions 128 and 64 respectively, combined with another 0.2 dropout layer, make up the new layer. Three class heads with a categorical cross entropy loss function made up the final layer.

- **ResNet-50**

ResNet is a neural network made up of pyramidal cells in the cerebral cortex. Residual neural networks accomplish this by exploiting skip connections, or shortcuts, to jump over a few layers. In deep neural networks, a residual gaining knowledge of framework allows to keep good consequences through a community with many layers.

One problem typically noted by experts is that with deep networks composed of many dozens of layers, accuracy can end up saturated, and some degradation can occur. There occurs a problem known as vanishing gradient in which the gradient fluctuations become too small to appear useful. The deep residual community offers with some of these problems by way of the usage of residual blocks, which take advantage of residual mapping to maintain inputs. By utilizing deep residual studying frameworks, engineers can test with deeper networks that have specific training challenges.

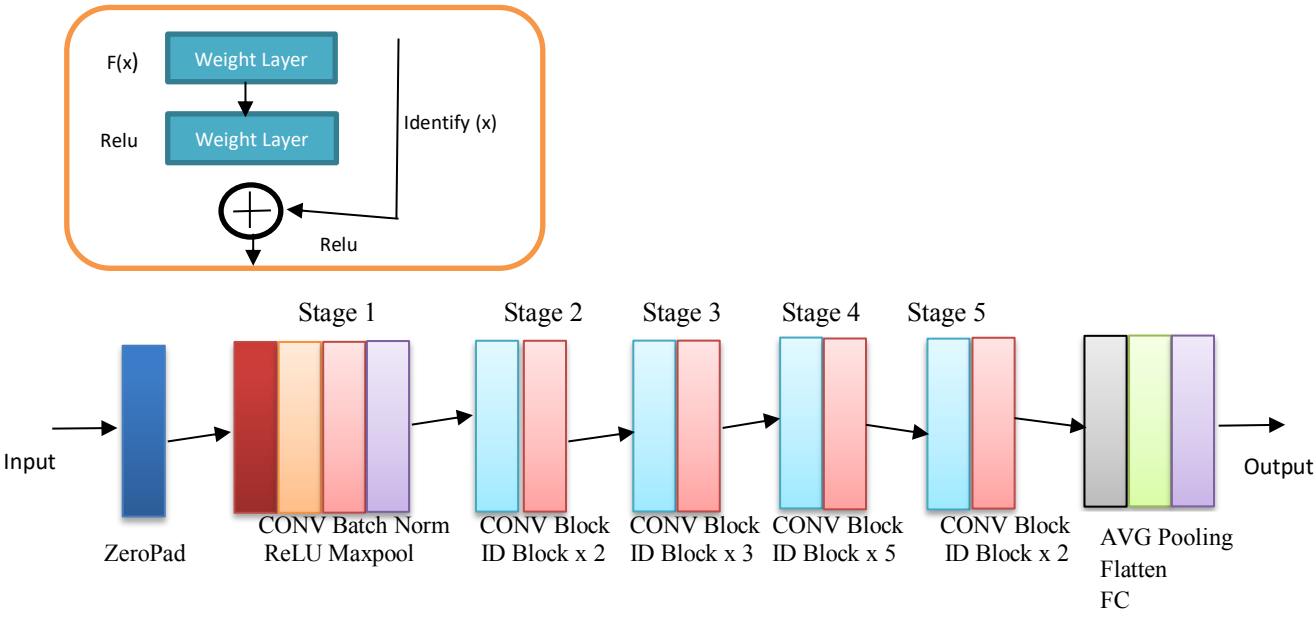


Figure 37: Residual Learning Block and Architecture of ResNet-50

Chapter 3
Proposed Model

We have implemented novel CNN Architecture using one basic convolutional neural network and one vgg16. The purpose of this study is whether a histopathological images of breast is impacted by cancer or not. Deep learning approaches have emerged as a standout artificial intelligence methodology in recent years, owing to their ability to discover complicated patterns within input data as well as develop proper classification tasks of the underlying data at various levels. We have developed and trained novel model and obtained their accuracy on a dataset. We have performed image augmentation before feeding it to the image classification model. All of the implementations have been performed on local system using the Keras module of TensorFlow. First, let's look over the image datasets used in this research.

3.1 Model Architecture:

In this study, we have used one convolutional neural network and one vgg16 model and then merge them to built a novel model. Let's discuss both models and then the merged model.

- **Model X - CNN Model**

This network was built in a similar fashion. It was built sequentially with three repetitions of convolutional and pooling layers, then a 0.2 dropout layer. Another convolutional and pooling layer along with flattening. A 3x3 kernel size is used in every convolutional layer. Finally, there are two fully connected layers of dimensions 128 and 64, that are ReLU activated, with a 0.2 dropout layer in between, and for the three-class classification, a softmax output layer was used.

- **Model Y – VGG16 model**

VGG16, a well-known deep learning model is chosen as a classifier, available in the TensorFlow library. This model has been used as a base for adding a new untrained head. The VGG16 is a Deep Neural Network architecture that is comprised of 2 convolutional filter layers and 1 pooling layer which is repeated twice. Then, 3 times, 4 convolutional filter layers and 1 pooling layer were applied. Lastly, 2 fully connected layers and then a softmax output.
The final layers of the pretrained network are discarded and replaced with new layers to meet the new classification task. A 0.2 dropout layer, a flatten, and two fully linked networks of dimensions 128 and 64 respectively, combined with another 0.2 dropout layer, make up the new layer. two class heads with a binary cross entropy loss function made up the final layer.

- **Concatenated Model using Model X and Model Y**

The proposed merged CNN architecture will be discussed in this section. Our proposed convolutional neural network model is a stack of convolutional layers, activation layers, dropout layers, and max pooling layers from vgg16 and basic CNN architecture. Then, at the feature level, we concatenated two parallel max-pooling layers of the same dimensions and performed convolution with the ReLU activation function on that concatenated layer. The output of convolution layers features will then be flattened. We added a 20% dropout layer to the proposed convolutional neural network to avoid over fitting. Finally, the classification task is performed by the final layer, which uses the softmax activation function.

Layer	Output shape	Param #
Input_1(input layer)	(48,48,3)	0
Zero_padding2d_3	(50,50,3)	0
Conv2d_layer	(17,17,64)	1792
Conv2d_layer	(6,6,64)	36928
Max_pooling2d_layer	(3,3,64)	0
Conv2d_layer	(1,1,128)	73856
Conv2d_layer	(1,1,128)	147584
Max_pooling2d_layer	(1,1,128)	0
Conv2d_layer	(1,1,256)	295168
Conv2d_layer	(48,48,16)	448
Conv2d_layer	(1,1,256)	590080
Max_pooling2d_layer	(24,24,16)	0
Conv2d_layer	(1,1,256)	590080
Conv2d_layer	(24,24,32)	4640
Max_pooling2d_layer	(1,1,256)	0
Max_pooling2d_layer	(12,12,32)	0
Conv2d_layer	(1,1,512)	1180160
Conv2d_layer	(12,12,64)	18496
Conv2d_layer	(1,1,512)	2359808
Max_pooling2d_layer	(6,6,64)	0
Conv2d_layer	(1,1,512)	2359808
Dropout	(6,6,64)	0
Max_pooling2d_layer	(1,1,512)	0
Conv2d_layer	(6,6,128)	73856
Conv2d_layer	(1,1,512)	2359808
Max_pooling2d_layer	2	0

Conv2d_layer	(1,1,512)	2359808
Conv2d_layer	(3,3,256)	295168
Conv2d_layer	(1,1,512)	2359808
Max_pooling2d_layer	(1,1,256)	0
Max_pooling2d_layer	(1,1,512)	0
Concatenate	(1,1,768)	0
Conv2d_layer	(1,1,128)	884864
Flatten	128	0
Dense	256	33024
Dropout	256	0
Dense	128	32896
Dense	2	258
Total params: 16,058,338		
Trainable params: 16,058,338		
Non-Trainable params: 0		

Table 5: Dimension of ConvNet

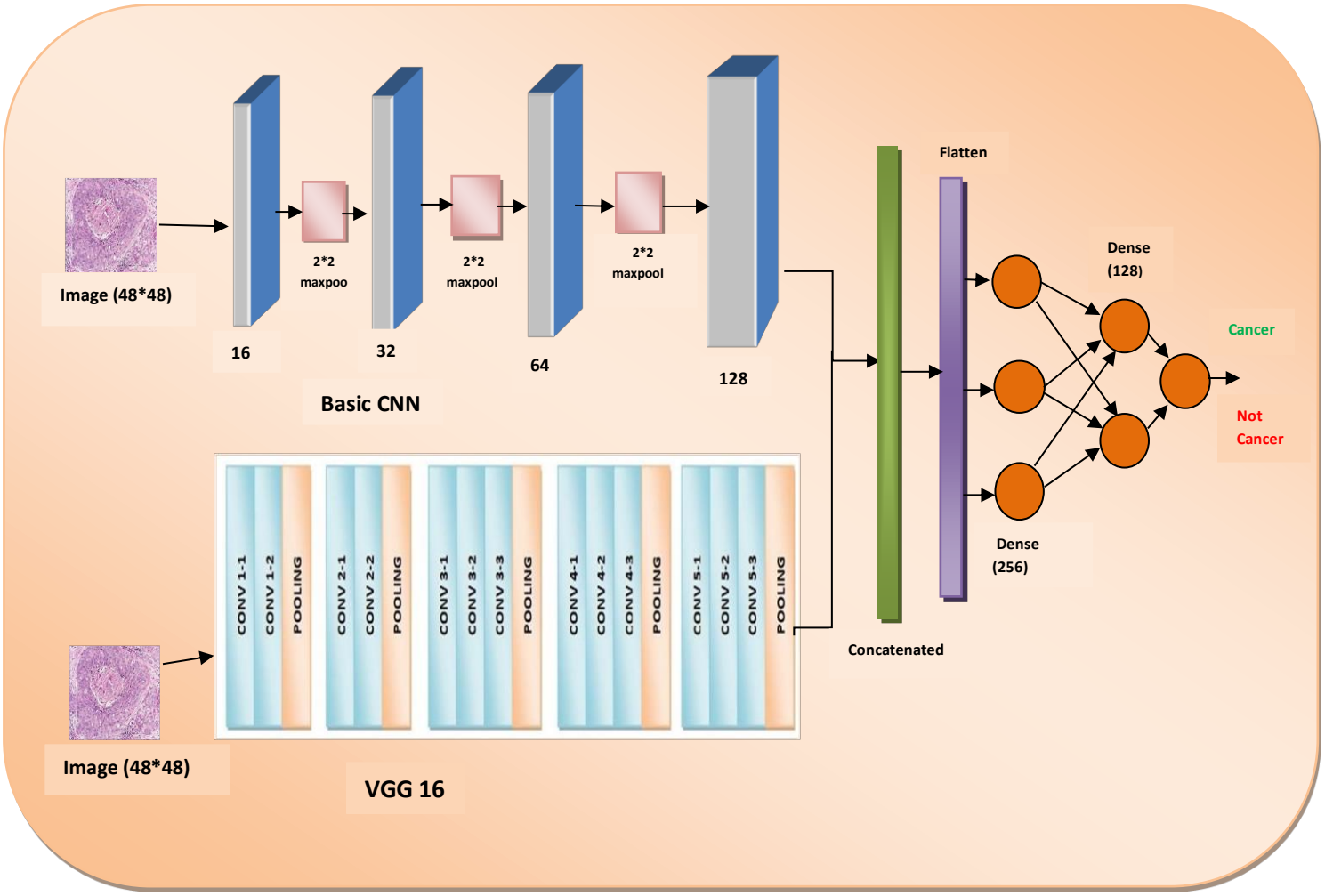


Figure 38: ConvNet Layered Architecture

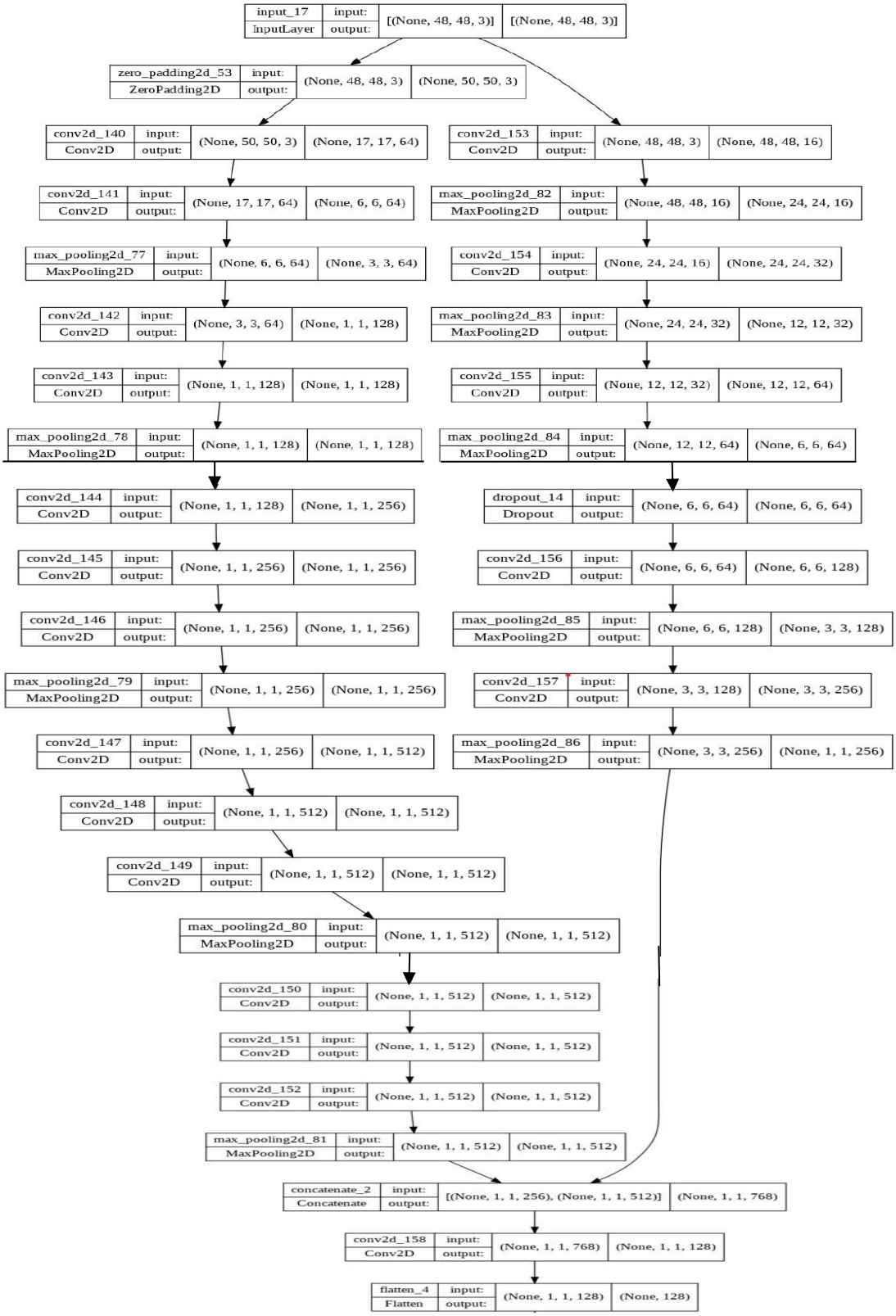


Figure 39: Flow of ConvNet Layered Architecture

Chapter 4
The Experimental Approach

In this chapter, we'll look at our proposed CNN model's experimental approach. This experiment was carried out with the following system configuration:

- Processor: AMD Ryzen 5000 series (5th Gen)
- RAM: 8GB
- Hard Disk: 512 GB
- Software Used: Anaconda, Jupyter.

4.1 Data analysis

Data analysis is the first stage with the purpose of conserving the best out of trash since it is the sequence of the process of analyzing, cleaning, converting, and modeling data with the goal of identifying important data, reporting conclusions, and supporting decision making. One of the main factors for data analysis is to determine the data's complexity and appearance, and to ensure that the data is legitimate as well as contains the required fields.

4.2 Dataset

We utilised the Kaggle and used dataset IDC regular (the breast cancer histology image dataset). We split the data (images) around 72% for Training purpose and 20% for Testing purpose and rest off these 8% data for validation. For example, in detection of breast cancer the histopathology dataset holds 2,77,524 patches from 162 whole mount slide images of breast cancer specimens scanned at 40x of size 50*50 was retrieved. 1,98,738 of them tested negative, while 78,786 tested positive. Filenames (image) in this dataset look like this "8863_idx5_x451_y1451_class0" where8863_idx5 represents patient id
x451 and y1451 represents x and y coordinates of the
crop0 represents class label.

We have performed image augmentation before feeding it to image classification model. Allof the implementations have been performed on local system using keras module of tensorflow.

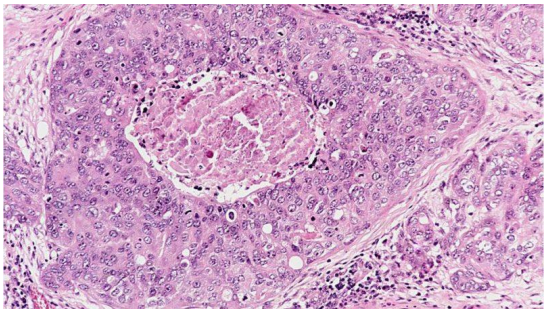


Figure 40: Cancer

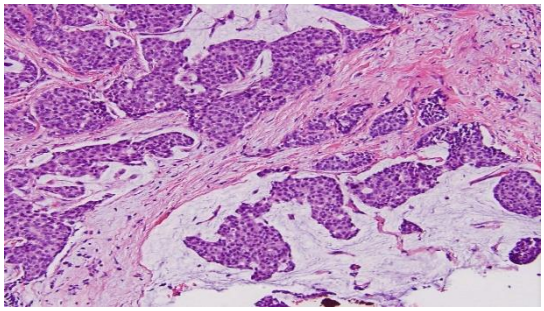


Figure 41: No Cancer

4.3 Model Training , Testing and Validation

	Cancer	No Cancer	Total
Train	143149	56669	199818
Test	39736	15769	55505
Validation	15853	6348	22201

Table 6: Train, Test and Validation dataset details

Chapter 5
Experimental Results

5.1 Model Evaluation

We use the following measurements based on confusion matrices conclusions for prediction evaluation.

5.1.1 Precision

Simply expressed, precision refers to the percentage of actual positive results out of the total positive anticipated by the model.

The following equation can be used to calculate precision values:

$$\text{Precision} = \frac{Sum\ x\ in\ X\ TruePositives\_x}{Sum\ x\ in\ X\ (TruePositives\_x + FalsePositives\_x)}$$

5.1.2 Recall

The rate at which the system is able to relearn information is referred to as recall. As an outcome, Recall estimates how many true positive (TP) traits our model identified and labeled as positive.

The following equation can be used to calculate recall values:

$$\text{Recall} = \frac{Sum\ x\ in\ X\ TruePositives\_x}{Sum\ x\ in\ X\ (TruePositives\_x + FalseNegatives\_x)}$$

5.1.3 F1-score

A significant number of True Negatives (TN), which in most business situations do not rely on much, contribute to the accuracy, although False Negatives (FN) and False Positives (FP) frequently have business consequences. If we need to find the right balance between Recall and Precision There is an unequal class distribution, F1-Score would be an appropriate statistic to utilize.

$$\text{F1-Score} = = 2 * \frac{Precision * Recall}{Precision + Recall}$$

5.1.4 Accuracy

The data that is correctly categorized divided by the whole dataset evaluated is how accuracy is calculated. It can also be calculated as a 1-error.
The following equation can be used to calculate the accuracy:

$$\text{Accuracy} = \frac{TruePositive(TP) + TrueNegative(TN)}{TruePositive(TP) + TrueNegative(TN) + FalsePositive(FP) + FalseNegative(FN)}$$

5.2 Model Prediction

After cleaning, preprocessing, and analyzing the data, the first action we do is integrate it into a model that generates probabilistic results. The confusion matrix is a performance metric for machine learning classification. Precision, Recall, Accuracy, Specificity, and, most importantly, AUC-ROC curves may all be calculated using the confusion matrix. It is used to evaluate machine learning classification performance.

By looking at the confusion matrix, we can determine various metrics for measuring the model we've utilized for the Cancer cases of the test dataset.

- Recall = $\frac{TP}{TP + FN}$

  =65%

- Precision = $\frac{TP}{TP + FP}$

  =75%

- F1-Score = 2 * $\frac{Precision * Recall}{Precision + Recall}$

  = 88%

- Accuracy = $\frac{TP + TN}{TP + TN + FP + FN}$

  =87.5%

	precision	recall	f1-score	support
0	0.93	0.89	0.91	39736
1	0.76	0.83	0.79	15769
accuracy			0.88	55505
macro avg	0.84	0.86	0.85	55505
weighted avg	0.88	0.88	0.88	55505

```
[[35526  4210]
 [ 2726 13043]]
Accuracy: 0.8750382848392037
Specificity: 0.8271291775001586
Sensitivity: 0.8940507348500101
```

Figure 42: Performance Matrix

It can be observed that the proposed model performed reasonably well with 93% precision and 89% recall in the classification task. Now moving on to the accuracy and F1-scores of the proposed model, the proposed model achieved the highest score with 87% accuracy and 91% F1-score. Figure below shows the comparison of the accuracy and loss during training & validation stages for each epoch, on the proposed model.

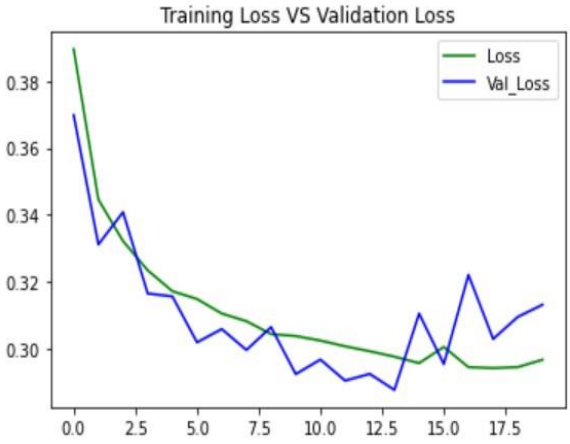


Figure 43: Training loss vs validation loss

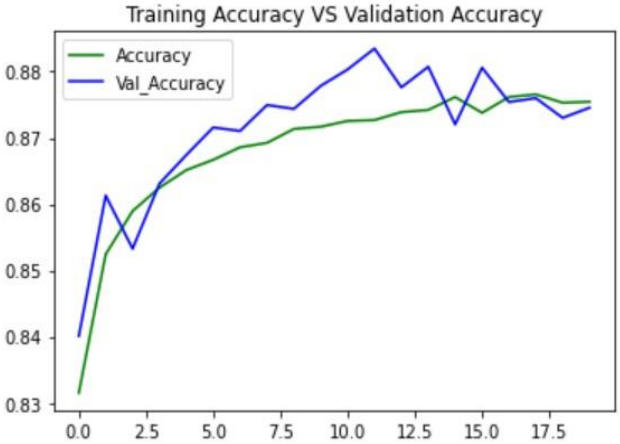


Figure 44: Training accuracy vs validation accuracy

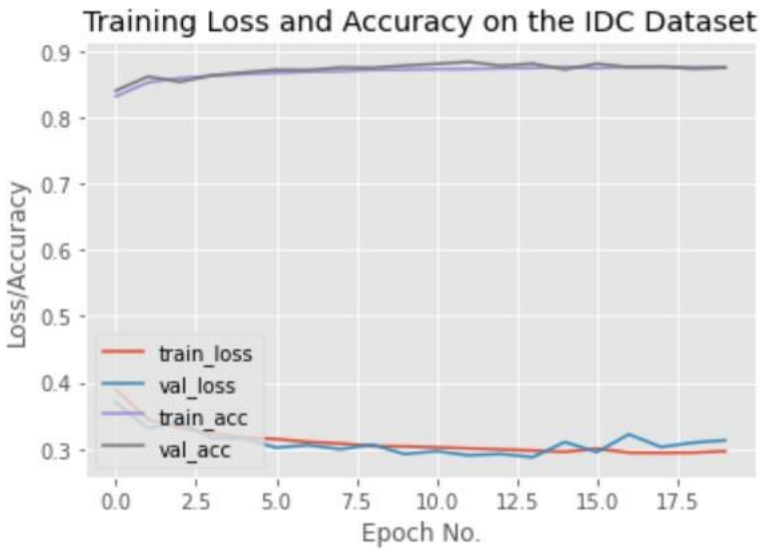


Figure 45: Training loss and accuracy

Chapter 6
Conclusion

The convolutional neural network model was successfully deployed on the dataset and produced of accuracy of around 87.00% in breast cancer diagnosed. The Kaggle was used to get the histopathological images and other image models for different cancer. As we've seen, our proposed model uses two different architecture one is basic CNN and another is VGG16 to effectively capture cancer, resulting in excellent classification. In future study, we aim to investigate more efficient results by using a larger and accurate dataset. We'll try using some more advanced deep learning models and combine those architecture to generate hybrid model with optimal hyperparameters to achieve greater accuracies and minimize loss and computationally time saving which will decrease the mortality rate.

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