**Detection of Breast Cancer from Ultrasound Imaging using Deep Learning Model**


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


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## APPROVAL

This Project titled **"Detection of Breast Cancer from Ultrasound Imaging using Deep Learning Model"**, submitted by Maruful Islam Raz and Sharmin Akter to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *4$^{th}$ February, 2023*.

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# DECLARATION

By submitting this document, we affirm that this project was completed by us under the direction of **Naznin Sultana, Associate Professor, Department of CSE** at Daffodil International University. Additionally, we assure that no portion of this project or any element of it has been submitted to another institution for the purpose of receiving a degree or certification.

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# ABSTRACT

The second most common cause of mortality for women is breast cancer. Female death rates can be decreased if breast cancer is found early. For early cancer detection, an automated system is needed because manual breast cancer diagnosis takes a long time. There is a 30% possibility that the disease can be treated with early identification, but late detection of advanced-stage malignancies makes therapy more challenging [1,2]. Using Deep learning, we created a model that can predict the likelihood of getting breast cancer. In this paper, deep learning models are used to provide a new framework for detecting breast cancer from ultrasound images. Images from the Breast Ultrasound Dataset are divided into three categories: normal, benign, and malignant. In order to increase the amount of the original dataset and improve Convolutional Neural Network (CNN) model learning, data augmentation is carried out. Uses of Model: VGG16, InceptionV3, Exception, DenseNet201. We used these 4 models in deep learning, among which the accuracy of inception is the best and the accuracy value is 88%.

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# CHAPTER 1
# INTRODUCTION

## 1.1 Introduction

Contrary, the major cause of mortality internationally is cancer. So when the body's cells begin to proliferate and convulse, cancer begins. Any section of the body's cells has the potential to transform into cancer, which can substantial portion to other organs. After skin cancer, breast cancer is the next most recurrent malignancy among women. After adolescence, breast cancer affects women in almost every country, but the likelihood of getting it rises with age. The most frequent cancer in the world right now is breast cancer. The disease prediction model used a convolutional neural network. With 7.8 million women still alive who had relapsed in the previous five years, breast cancer was the most common cancer in the world in 2020. The American Cancer Society has the accompanying projections for breast cancer in the US in 2021: 281,550 new variants of invasive breast cancer in women will be recorded, and 43,600 of those cases will be fatal. In Bangladesh, breast cancer appears to be the most prevalent and lethal type of cancer in women. As the cause of 69 percent of deaths among women, it has turned into an unspoken burden. In Bangladesh, there were 22.5 new cases of breast cancer per 100,000 females. Bangladeshi women aged 15 to 44 have been shown to have the highest prevalence incidence of breast cancer (19.3 per 100,000). The preponderance of breast cancers spreads in one to two months, so by the time you detect a lump, the disease has already been present in your body for two to five years. As a logical conclusion, we cannot afford to ignore this illness. Where deep learning is helpful in this situation. The age of data is currently upon us. However, data are only helpful when they are processed and put to use. The same thing is carried out through deep learning. Deep learning, which functions without human involvement based on training and experience, is a part of the artificial intelligence framework. The application of deep learning in healthcare is highly successful and promising [5]. Therefore, if we can analyze the historical information of breast cancer patients and apply deep learning to them, then our technology can forecast whether a person will have breast cancer or not in the future, thereby saving that person's dignity as well as the survival of countless other people. Early breast cancer symptoms may go unnoticed since they are similar to those of other illnesses. So, when thinking about future health, detection is an important step to take into account. This is the reason we considered developing a deep learning-based model that could collect information from the user and determine if the user had a chance of having breast cancer or not. Although relatively uncommon, breast cancer in young or old age is quite sad. Therefore, taking action to combat breast cancer is sensible, and the first step we can take is early identification of the disease, which relies in large part on deep learning. Making a deep-learning model that can forecast the likelihood of breast cancer is the goal of this research.

## 1.2 Motivation

The World Health Organization estimates that there will be 2.3 million cases of breast cancer and 685 000 deaths in 2020. In Bangladesh, 22.3 per 100000 females of all ages suffered from breast cancer. For ages between 15 to 44 years, the rates increase, estimated to be 19.3 per 100000. Untreated breast cancer can lead our anxiety, and depression. Bangladesh isa developing country. The cost we need to bear for the treatment of breast cancer in Dhaka is about 6.5 lakh BDT, which is increasing day by day. But the majority of individuals in our community struggle with poverty. Consequently, detection is a vital step to take into account for both health and economic prospects. This is the rationale for our decision to establish a deep learning-based model that can determine whether a patient is inclined to get breast cancer or not. Although relatively uncommon, breast cancer in any era is extremely sad. Therefore, taking action to combat this ailment is fair, and the very first step we can take is early detection utilizing deep learning. We were compelled to do this research because we are deep learning researchers.

## 1.3 Research Questions

How can we harness the Wisconsin Breast Cancer Comprehensive dataset to foretell breast cancer so that sufferers may swiftly take the necessary precautions and live healthier lives? this is the sole question addressed by this study, and as computer science students, deep learning has asked to give the remedy.

## 1.4 Expected Output

We pre-process the data after collecting it. Then we'll use the algorithm we've chosen. One or two of the applicable algorithms may provide the best results for predicting Breast Cancer.

## 1.5 Project Management and Finance

This is our initiation of a project into the subject. That's why deciding which dataset to use and how to proceed was so difficult for us. Our supervisor's modest mentorship is greatly appreciated. We gathered data from the UCI Deep Learning Repository and completedthe study flawlessly under the supervision of our supervisor. As for the data, it was gatheredvia the internet, as was other study material. We are completing the project at no cost to anyone**.**

## 1.6 Report Layout

i. We talked about our research in Chapter 1. This section contains a quick introduction to the project as well as our motivation for undertaking it. There is also information on what the major motivation is and how to handle our research effort.

ii. We examined the research's basis in Chapter 2. This section also includes an overview of the results of other research publications as well as a comparison of those research efforts. You can also learn about the scope of the problem and the difficulties we encountered while doing the research.

iii. We spoke about our research methods in Chapter 3. This chapter covers which instruments are required for the study, how we obtained data, statistical analysis of the dataset, and proposed approach.

iv. In Chapter 4, we examined the algorithms utilized in this study, how they were applied, and how the algorithms' results were summarized.

v. In Chapter 5, we explored the project's social impact and long-term viability.

vi. Finally, in Chapter 6, we wrap up our research and reach a conclusion.

# CHAPTER 2
# BACKGROUND

## 2.1 Terminologies

Terminology refers to the specialized words and phrases that are used in a particular field or profession.

## 2.2 Breast Cancer

Breast carcinoma in which the cells there rapidly and uncontrolled proliferate. The cells located in the breast that turn cancerous determine it. In fact, breast cancer can start anywhere in the breast. Each of a breast's three portions is autonomous. The lobules, ducts, and connective tissue are a few of these structures. Breast cancers tend to begin in the conduits of the temporalis.

Through lymph and blood arteries, breast cancer can spread outside of the breast. It has been commonly recognized to have proliferated. The most notable ones of breast cancer entail:

1. Invasive ductal carcinoma: This form of cancer starts in the ducts eventually growing and spreading outside of them to other parts of the breast.
2. Invasive lobular carcinoma: The above cancer cell begins in the lobules and accumulatesto nearby breast tissues. The most dangerous aspect is that it can spread to other parts of the body.

Breast cancer is the next most frequent malignancy in women after skin cancer. Breast cancer affects almost entirely women in the majority of cases, but men can get it as well. It refers to a malignant tumor that has arisen from breast cells. But the main fact we felt or x-ray scan shown the breast tumor as a lump. Most of the breast lumps are benign and malignant (not-cancer).

### 2.2.1. Artificial Intelligence

Artificial intelligence (AI) is the ability of a machine or technology to learn from experience and analogies in a bid to imitate the capacities of the human intellect. The main goalof Artificial Intelligence is to make a computer which can automatically learn, plan and solve problem. Though we tried to more than a half century, AI still hasn't shown us that much progress. We are still unable to make the computer as intelligent as human being. But in recent year Artificial Intelligence shown us a great potential. And the used of AI is increasing day by day.

### 2.2.2. Machine Learning

An application or subset of artificial intelligence, also abbreviated as AI, is machine learning. The principle of Machine Learning is by which a computer can learn fromprevious data, recognizing patterns and able to make proper decision with no help from human. Merging numerical statistics and predictive analysis provides machine learning.
The use of Machine Learning on ML in health care is very promising and effective [5].
Machine learning is a facet or application of artificial intelligence, typically referred to as AI.

1. The model is trained using the supervised learning method on either a dataset with labels or a dataset including both input and output parameters. There are many supervised learning algorithms, except Nave Bayes, Decision Trees, and Linear Regression. Learning.

2. Unsupervised Learning: In Unsupervised Learning, the model learns how to categorize data that is provided without output parameters. K-Means Clustering isan example of an unsupervised learning algorithm.

3 Reinforcement Learning: In this algorithm we use a agent. By using his own behaviorsand experiences, the agent learns in an interactive environment which is input on it.

## 2.3 Related Works

The synopsis of a few related scholarly articles that were pertinent to and beneficial to our study are stated underneath.

Hiba Asri et al. [6] adopted support vector machine (SVM), decision tree (C4.5), naive bayes (NB), and K - Nearest Neighbors (K-NN) for breast prognosis on the Wisconsin Breast Cancer (Original) set of data. They probably done a great deal of pre-processing on the data. The support vector machine (SVM), out of the methods listed, offered the maximum accuracy while having the lowest margin of error.

As a consequence, they were able to arrive at reliable estimate. However, there are still numerous algorithms that could provide us with much high clarity than this. We explored for other publications that had achieved substantially greater precision because of this.

During the Wisconsin breast cancer dataset, Md. Toukir Ahmed et al.[7] adopted Naive Bayes, Support vector machine (SVM), Multilayer perception (MLP), J48, and Random Forest for breast cancer prediction. Performance metrics, including Accuracy, Kappa statistic, precision, recall, F-measure, MCC, and ROC area, were utilized to compare the results. Naive Bayes among them exhibited the best findings. We tend to look for others.

Borges et.al.[8] analysis the Wisconsin Breast cancer dataset using deep learning for breast cancer detection. In this process they used only two algorithms. That's are the Bayesian Networks algorithm and J48. Among them the Bayesian Networks algorithm achieved the best accuracy.

Vikas Chaurasia el al. [9] also worked in Wisconsin breast cancer dataset. They used only three algorithms which were the Naïve Bayes, RBF Networks and J48. Among this three algorithms Naïve Bayes was the best predictor. This 4 paper's generalization ability was potentially high. But there are still many algorithms that need to be validated. This is the territory and theme that we opted for this analysis.

## 2.4 Comparative Analysis and Summary

We were unable to perform study in a specific area because we obtained our data from an internet resource, the UCI Deep Learning repository. We've categorized all of the research papers we've looked at into one category. The entire study was based on the Wisconsin Breast Cancer dataset. This dataset has been the subject of a lot of research. However, there is a lot of opportunity for development. Many algorithms that could produce substantially better results were not used in the test. That is why I chose the finestalgorithm that might provide us with the greatest results. This is where I believe my research will be useful.

## 2.5 Scope of the Problem

After perusing the aforementioned research studies, it is undeniable that one of the most preferred study issues is the prediction and diagnosis of breast cancer using deep learning. We can also see that there is still much room for improvement. We can proceed even though we consider there is still a ton of opportunity for investigation on this subject.

## 2.6 Challenges

Collecting information on breast cancer patients appeared to be the most arduous part of the study. We couldn't gather data personally because to the COVID-19 epidemic, and if we did, we'd have to conduct the survey while taking a lot of health risks. Our supervisor, on the other hand, was gracious enough to provide us with the opportunity to use an online dataset. However, there are numerous and diverse datasets on Breast Cancer. It was a little more difficult to get the right and suitable dataset because this was our first research on Breast Cancer and we didn't know much about it. However, with the assistance of our supervisor,we were able to overcome this obstacle.

# CHAPTER 3

# RESEARCH METHODOLOGY

## 3.1 Research Subject and Instrumentation

This inquiry is based on historical data concerning breast cancer. This data was compiled online. Python was the programming language we incorporated for analysis and model creation, and Google Colab and Jupyter Notebook served as the runtime environment.

## 3.2 Data Collection Procedure

The Wisconsin breast cancer (Original) dataset is what it is regarded as [11]. Everyone may use this dataset for study [12]. This dataset contains 684 records in total. There are eleven qualities. The first property, which is the ID number, is not necessary for research. That is why we took it out of the dataset. The number 10, which has the beliefs 2 and 4, was utilized to symbolize the class value. Where two stands for benign cancer and malignant cancer for four. The remaining characteristics are numbered from one to ten.

## 3.3 Data Pre-Processing

I. The Collecting information on breast cancer patients appeared to be the most arduous part of the study .One of the most significant roadblocks to building a good model is null values. There are numerous options for resolving this issue. One of them is to take the meanvalue of the null-valued feature. However, there are no null values in the dataset I have.

II. I tested whether or not my dataset was imbalanced in the following step of data pre-processing. A dataset that has a considerable margin of unequal target class distribution is said to be unbalanced.

III. Data pre-processing requires finding correlations between the feature space and the independent aspects and, in the long run, prediction accuracy. It's also crucial for comprehending the dataset's features.

IV. Rescaling multiplies the height and width of the image by a scaling factor. If the scaling factor is not identical in the vertical and horizontal directions, then rescaling changes the spatial extents of the pixels and the aspect ratio.

V. 3-D array representing a single color or multispectral image. 3-D array representing a stack of grayscale images. 4-D array representing a stack of images.

## 3.4 Proposed Methodology

Proposed methodology refers to the approach or plan that is suggested or put forward for achieving a particular goal. In research, the proposed methodology refers to the methods and techniques that will be used to conduct the research and achieve the research objectives. The proposed methodology should be carefully planned and clearly described in a research proposal or study design. It should be based on a thorough review of the literature and should be appropriate for the research question being addressed. The proposed methodology should also be feasible, meaning that it can be realistically carried out with the resources and time available.

The proposed methodology should be described in detail, including the specific methods and techniques that will be used, the sample size and sampling method, the data collection and analysis procedures, and any potential limitations or biases that may impact the results. It is important to be as transparent as possible in describing the proposed methodology, as this allows other researchers to understand and evaluate the validity and reliability of the study.

We have used 04 models in our study. They are: Inception V3, VGG16, Xception and DensNet201.

Here is the diagram of our proposed model.

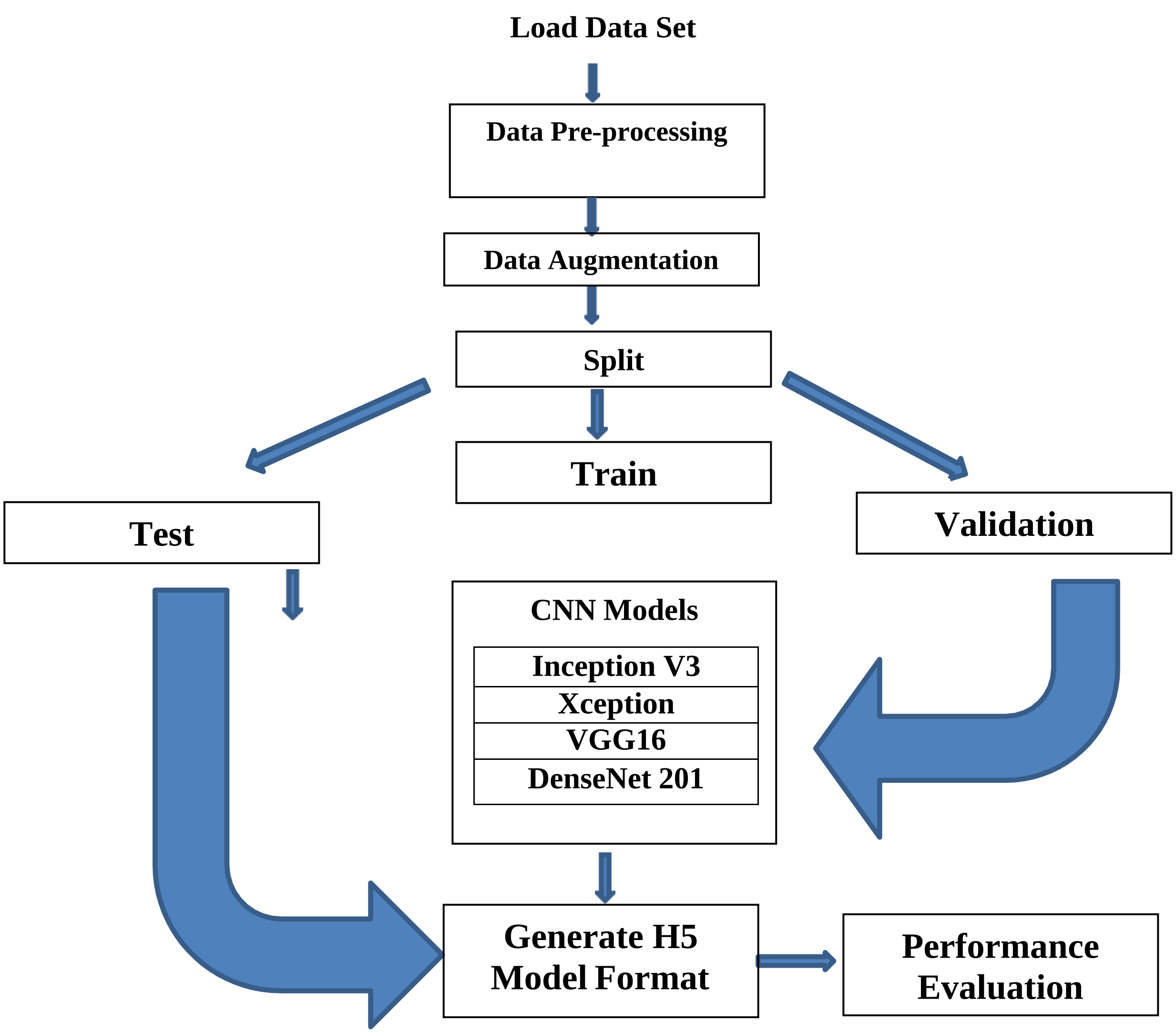



Figure3.4: Proposed Model Structure

## 3.5 Model Used

Using Deep learning, we created a model that can predict the likelihood of getting breast cancer. In this paper, deep learning models are used to provide a new framework for detecting breast cancer from ultrasound images. Images from the Breast Ultrasound Dataset are divided into three categories: normal, benign, and malignant. In order to increase the amount of the original dataset and improve Convolutional Neural Network (CNN) model learning, data augmentation is carried out. Uses of Model: VGG16, InceptionV3, Exception, DenseNet201. We used these 4 models in deep learning.

### 3.5.1 Inception V3

Inception v3 is a convolutional neural network architecture developed by Google and introduced in the paper "Rethinking the Inception Architecture for Computer Vision" (Szegedy et al., 2015). The architecture was designed for image classification and has achieved state-of-the-art results on the ImageNet dataset.

#### 3.5.1.1 Architecture of Inception v3

Here is a diagram of the Inception v3 architecture:

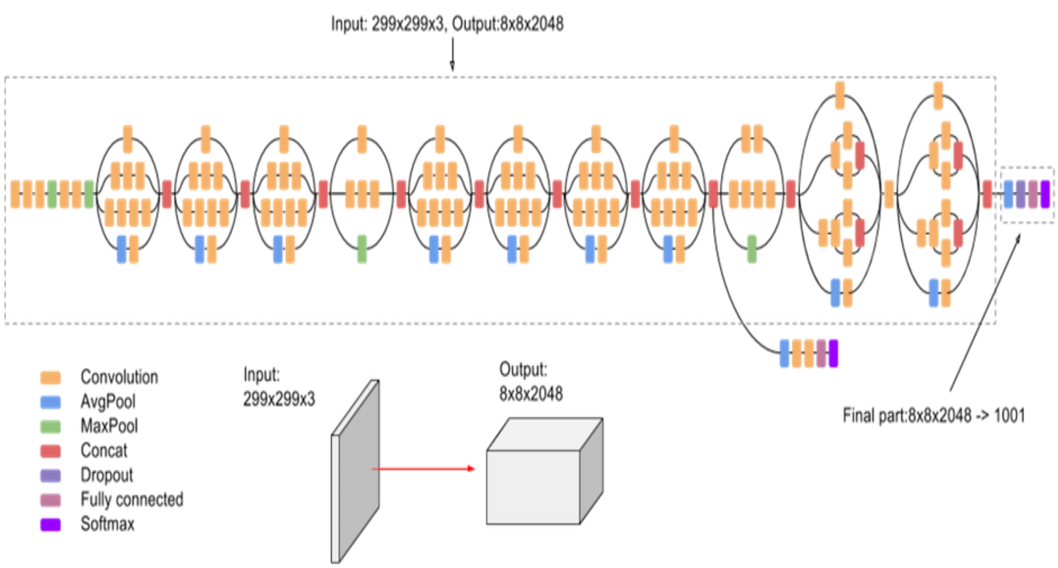



Figure: 3.5.1.1 Architecture of Inception v3

The Inception v3 architecture consists of a stack of modules, where each module consists of a series of convolutional, pooling, and normalization layers. The input to the network is passed through a stem, which consists of a series of convolutional and pooling layers that reduce the resolution of the input image. The output of the stem is then passed through a series of inception modules, which are blocks of layers that use a combination of 1x1, 3x3, and 5x5 convolutions to extract features from the input tensor at multiple scales. The output of the inception modules is then passed through a series of fully connected layers, which perform classification on the extracted features.

### 3.5.1.2 Input pipeline of Inception v3

The input pipeline for Inception v3 typically involves preprocessing the input images before they are fed into the network. This preprocessing includes steps such as resizing the images to a fixed resolution, cropping the images to a square, and normalizing the pixel values.

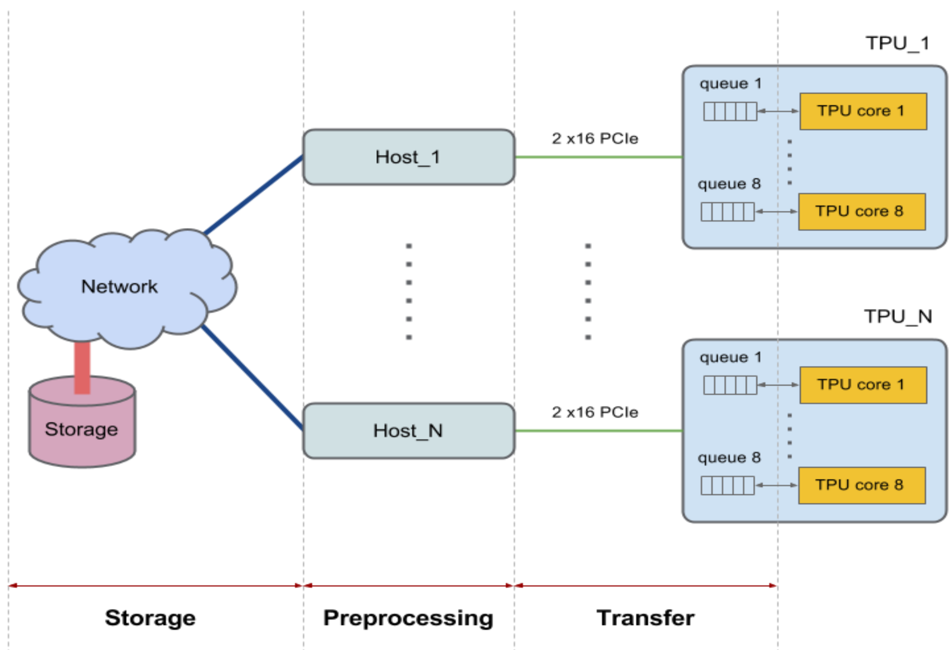



Figure 3.5.1.2 Input pipeline of Inception v3

After the images have been preprocessed, they are passed through the network in the form of a tensor, where they are convolved and down-sampled through a series of convolutional, pooling, and normalization layers. The tensor is then passed through a series of inception modules, which are blocks of layers that use a combination of 1x1, 3x3, and 5x5 convolutions to extract features from the input tensor at multiple scales. The output of the inception modules is then passed through a series of fully connected layers, which perform classification on the extracted features. The final output of the network is a probability distribution over the classes, indicating the likelihood that the input image belongs to each class. The Inception v3 architecture also includes auxiliary classifiers, which are additional fully connected layers that are trained to predict the class of the input image and are integrated into the network at intermediate layers. These auxiliary classifiers can help improve the overall performance of the network by providing additional supervision during training (Szegedy et al., 2015).

#### 3.5.1.3 Performance of Inception v3

Inception v3 is a convolutional neural network architecture that was developed for image classification and has achieved state-of-the-art results on the ImageNet dataset.

On the ImageNet dataset, Inception v3 achieved an error rate of 3.46% on the validation set and 3.58% on the test set, which was the best performance at the time of its publication (Szegedy et al., 2015). Inception v3 was also able to outperform other state-of-the-art models on a variety of other image classification benchmarks, including the COCO dataset and the Google Landmarks dataset. In addition to its impressive performance on image classification tasks, Inception v3 has also been used for other computer vision tasks such as object detection, segmentation, and face recognition. In these tasks, Inception v3 has also achieved strong performance and has been widely adopted by researchers and practitioners. Overall, Inception v3 has demonstrated strong performance on a variety of image classification and computer vision tasks and has become a widely used model in the field.

### 3.5.2 VGG16

VGG16 is a convolutional neural network architecture developed by Karen Simonyan and Andrew Zisserman and introduced in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition" (Simonyan & Zisserman, 2014). The architecture is known for its simplicity and has been widely used as a benchmark for image classification and object.

### 3.5.2.1 Architecture of VGG16

Here is a diagram of the VGG16 architecture:

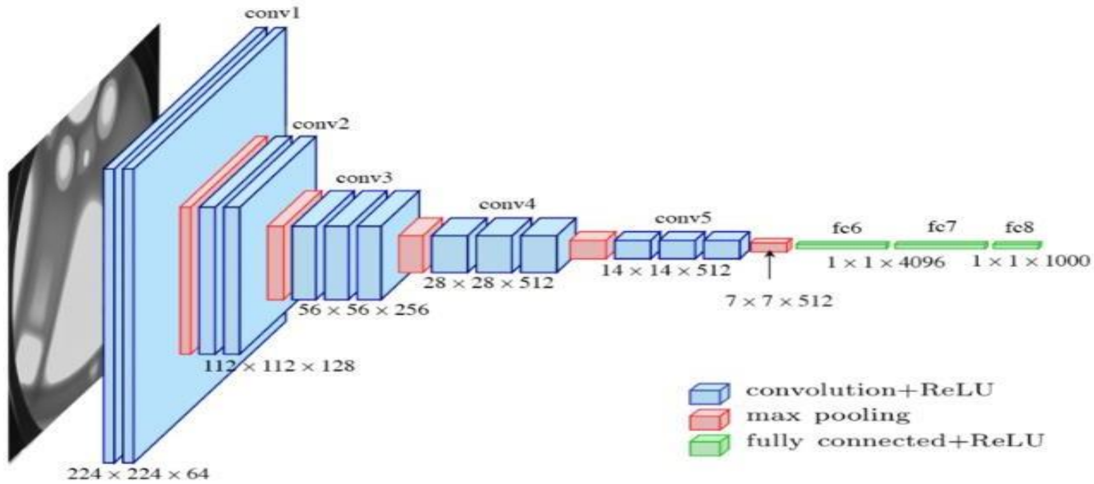



Fig: 3.5.2.1 Architecture of VGG16

The VGG16 architecture consists of a series of convolutional and max pooling layers, followed by a few fully connected layers. The input to the network is an image, which is passed through the convolutional and max pooling layers to extract features. The extracted features are then passed through the fully connected layers, which perform classification on the features.

VGG16 has achieved strong performance on a variety of image classification benchmarks, including the ImageNet dataset. On the ImageNet dataset, VGG16 achieved a top-5 error rate of 7.3% (Simonyan & Zisserman, 2014).

### 3.5.2.2 Input pipeline of VGG16

The input pipeline for VGG16 typically involves preprocessing the input images before they are fed into the network. This preprocessing includes steps such as resizing the images to a fixed resolution, cropping the images to a square, and normalizing the pixel values.

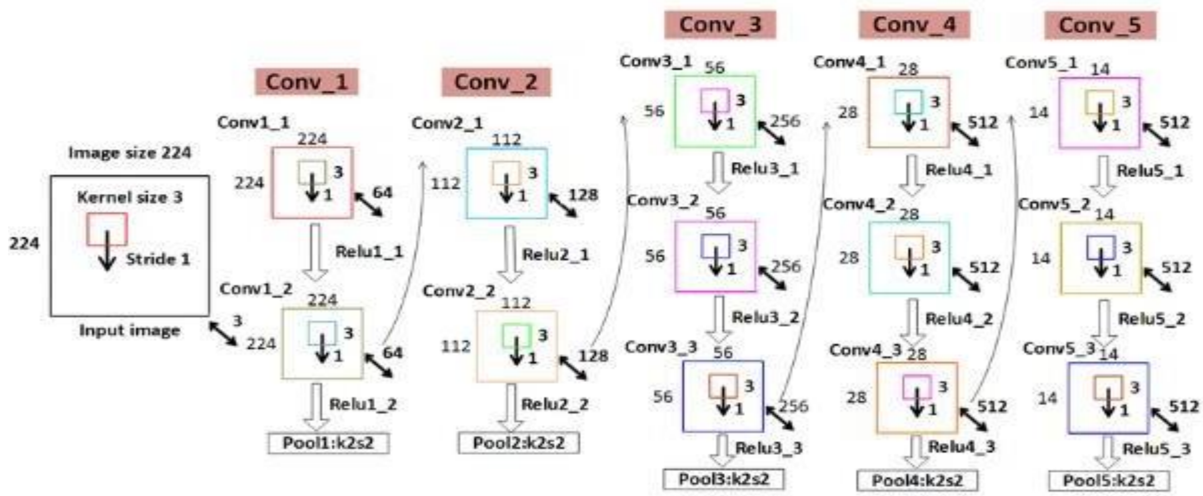



Figure 3.5.2.2 Input pipeline of VGG16

After the images have been preprocessed, they are passed through the network in the form of a tensor, where they are convolved and downsampled through a series of convolutional and max pooling layers. The tensor is then passed through a series of fully connected layers, which perform classification on the extracted features.

The final output of the network is a probability distribution over the classes, indicating the likelihood that the input image belongs to each class.

In addition to the main classification branch of the network, VGG16 also includes a branch for localization, which is trained to predict the bounding box coordinates of an object in the input image. The localization branch is made up of additional convolutional and fully connected layers that are added onto the main classification branch of the network.

### 3.5.2.3 Performance of VGG16

VGG16 is a convolutional neural network architecture that has been widely used as a benchmark for image classification and object detection tasks. VGG16 has achieved strong performance on a variety of image classification benchmarks, including the ImageNet dataset. On the ImageNet dataset, VGG16 achieved a top-5 error rate of 7.3% (Simonyan & Zisserman, 2014). VGG16 has also been used as a base model for a number of state-of-the-art object detection models, such as the Single-Shot Detector (SSD) and the You Only Look

Once (YOLO) detector. In addition to its strong performance on image classification tasks, VGG16 has also been used for other computer vision tasks such as image segmentation and face recognition. In these tasks, VGG16 has also achieved good performance and has been widely adopted by researchers and practitioners. Overall, VGG16 has demonstrated strong performance on a variety of image classification and computer vision tasks and has become a widely used model in the field.

### 3.5.3 Xception

Xception is a convolutional neural network architecture developed by François Chollet and introduced in the paper "Xception: Deep Learning with Depthwise Separable Convolutions" (Chollet, 2017). The architecture is an extension of the Inception architecture and is designed for image classification tasks.

#### 3.5.3.1 Architecture of Xception

Here is a diagram of the Xception architecture:

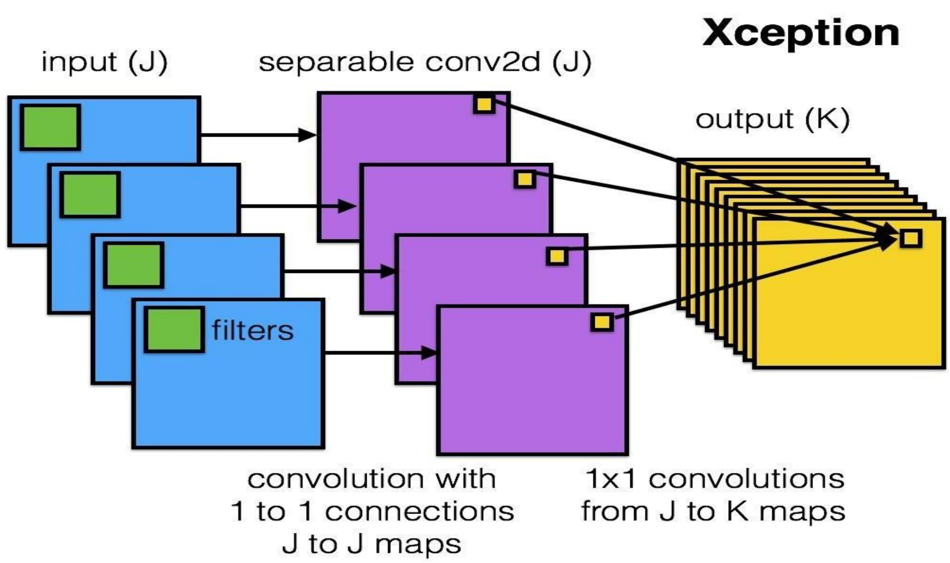



Figure 3.5.3.1: Architecture of Xception

The Xception architecture consists of a stack of modules, where each module consists of a series of depthwise separable convolutions and pointwise convolutions. Depthwise separable convolutions are a type of convolution that applies a single filter to each input channel, followed by a pointwise convolution that combines the output of the depthwise convolution across all channels. This allows the network to learn more efficient representations of the input while reducing the number of parameters. The input to the network is passed through a stem, which consists of a series of convolutional and pooling layers that reduce the resolution of the input image. The output of the stem is then passed through a series of Xception modules, which are blocks of layers that use depthwise separable convolutions to extract features from the input tensor at multiple scales. The output of the Xception modules is then passed through a series of fully connected layers, which perform classification on the extracted features. Xception has achieved state-of-the-art performance on a number of image classification benchmarks, including the ImageNet and COCO datasets.

### 3.5.3.2 Input pipeline of Xception

The input pipeline for a convolutional neural network typically involves preprocessing the input images before they are fed into the network. This preprocessing includes steps such as resizing the images to a fixed resolution, cropping the images to a square, and normalizing the pixel values.

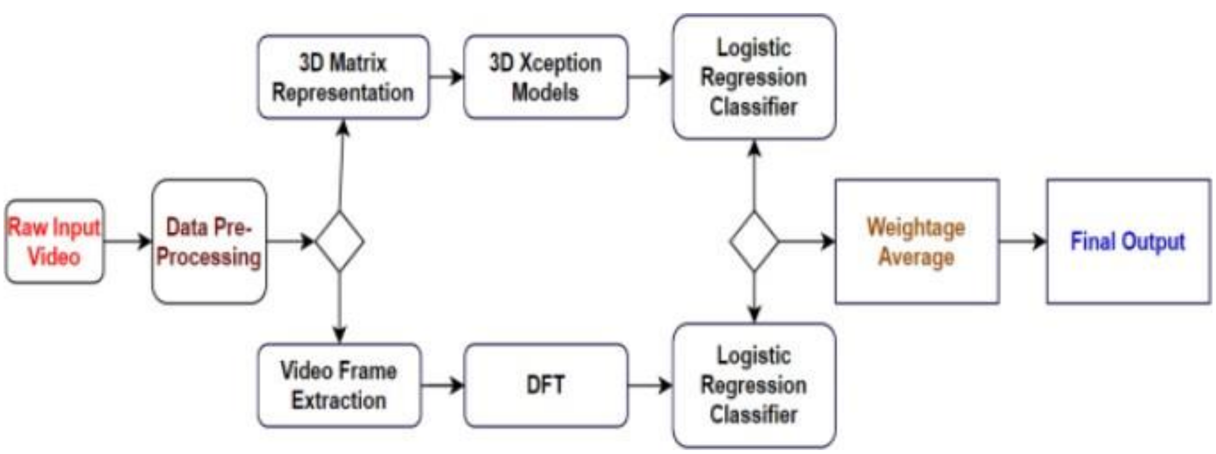



Figure 3.5.3.2: Input pipeline of Xception

After the images have been preprocessed, they are passed through the network in the form of a tensor, where they are convolved and downsampled through a series of convolutional, pooling, and normalization layers. The tensor is then passed through a series of fully connected layers, which perform classification on the extracted features. The final output of the network is a probability distribution over the classes, indicating the likelihood that the input image belongs to each class. In addition to the main classification branch of the network, some architectures also include a branch for localization, which is trained to predict the bounding box coordinates of an object in the input image. The localization branch is made up of additional convolutional and fully connected layers that are added onto the main classification branch of the network.

#### 3.5.3.3 Performance of Xception

Xception is a convolutional neural network architecture developed for image classification tasks and has achieved state-of-the-art performance on a number of benchmarks. On the ImageNet dataset, Xception achieved an error rate of 21.8% on the validation set and 21.9% on the test set, which was the best performance at the time of its publication (Chollet, 2017). Xception has also achieved state-of-the-art performance on the COCO dataset, a large-scale dataset for object detection and segmentation. In addition to its strong performance on image classification tasks, Xception has also been used for other computer vision tasks such as object detection and face recognition. In these tasks, Xception has also achieved good performance and has been widely adopted by researchers and practitioners. Overall, Xception has demonstrated strong performance on a variety of image classification and computer vision tasks and has become a widely used model in the field.

### 3.5.4 DenseNet201

DenseNet-201 is a convolutional neural network architecture developed by Gao Huang et al. and introduced in the paper "Densely Connected Convolutional Networks" (Huang et al., 2016). The architecture is known for its ability to efficiently learn deep networks and has been widely used for image classification and segmentation tasks.

### 3.5.4.1 Architecture of DenseNet201

Here is a diagram of the DenseNet-201 architecture:

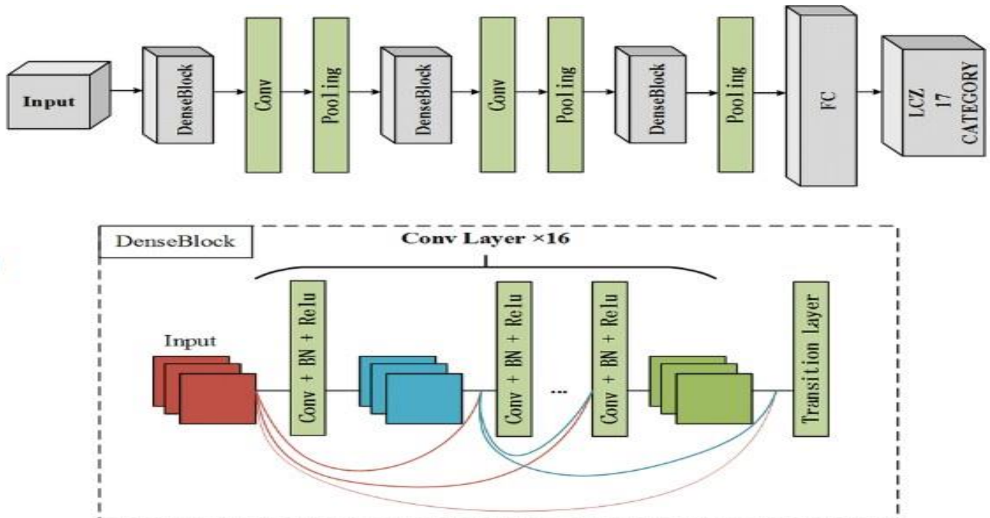



Figure 3.5.4.1: Architecture of DenseNet201

The DenseNet-201 architecture consists of a series of dense blocks, where each dense block contains a series of convolutional layers that are densely connected to the preceding layers. In a dense block, each layer receives the feature maps of all preceding layers as input, allowing the network to learn more efficient representations of the input. The output of the dense blocks is then passed through a series of transition layers, which reduce the resolution of the feature maps and increase the number of channels. The input to the network is an image, which is passed through the dense blocks and transition layers to extract features. The extracted features are then passed through a global average pooling layer and a fullyconnected layer, which perform classification on the features. DenseNet-201 has achieved strong performance on a variety of image classification benchmarks, including the ImageNetdataset. On the ImageNet dataset, DenseNet-201 achieved a top-1 error rate of 22.3% and a top-5 error rate of 6.3% (Huang et al., 2016).

### 3.5.4.2 Input pipeline of DenseNet201

The input pipeline for DenseNet-201 typically involves preprocessing the input images before they are fed into the network.

This preprocessing includes steps such as resizing the images to a fixed resolution, cropping the images to a square, and normalizing the pixel values.

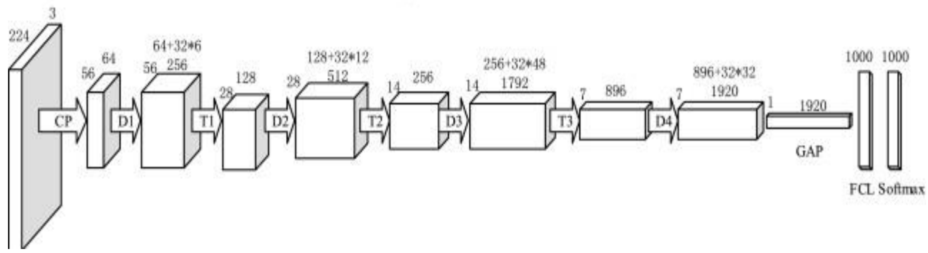



Figure 3.5.4.2: Input pipeline of DenseNet201

After the images have been preprocessed, they are passed through the network in the form of a tensor, where they are convolved and down sampled through a series of dense blocks and transition layers. The tensor is then passed through a global average pooling layer, which reduces the resolution of the feature maps, and a fully connected layer, which performs classification on the extracted features. The final output of the network is a probability distribution over the classes, indicating the likelihood that the input image belongs to each class. In addition to the main classification branch of the network, some architectures also include a branch for localization, which is trained to predict the bounding box coordinates of an object in the input image. The localization branch is made up of additional convolutional and fully connected layers that are added onto the main classification branch of the network.

### 3.5.4.3 Performance of DenseNet201

DenseNet-201 is a convolutional neural network architecture that has been widely used for image classification and segmentation tasks. DenseNet-201 has achieved strong performance on a variety of image classification benchmarks, including the ImageNet dataset. On the ImageNet dataset, DenseNet-201 achieved a top-1 error rate of 22.3% and a top-5 error rate of 6.3% (Huang et al., 2016). DenseNet-201 has also been used as a base model for a number of state-of-the-art image segmentation models. In addition to its strong performance on image classification tasks, DenseNet-201 has also been used for other computer vision tasks such as object detection and face recognition. In these tasks, DenseNet-201 has also achieved good performance and has been widely adopted by researchers and practitioners. Overall, DenseNet-201 has demonstrated strong performance on a variety of image classification and computer vision tasks and has become a widely used model in the field.

# CHAPTER 4

# EXPERIMENTAL RESULTS AND DISCUSSION

## 4.1 Experimental Result

An experimental result is the outcome of a scientific experiment or study. It is the observation or measurement that is made during the experiment, and it is used to test a hypothesis or to support or refute a theory. Experimental results are typically reported in the form of data, and they are analyzed using statistical techniques to determine their significance and to draw conclusions about the hypothesis being tested. Experimental results are an important part of the scientific process, as they allow scientists to understand the world around them and to make new discoveries.

## 4.2 Train loss and validation loss of Model

In deep learning, "loss" refers to the error or difference between the predicted output and the true output of a model. "Train loss" and "validation loss" are terms used to describe the error of a model on different datasets.

"Train loss" is the error of a model on the training dataset, which is the dataset used to train the model. This error is used to update the model's weights and biases during training, in order to minimize the error and improve the model's performance.

"Validation loss" is the error of a model on a separate validation dataset, which is not used for training. This error is used to evaluate the model's performance during training and tune the model's hyper parameters, such as the learning rate or the regularization strength.

It is important to monitor both the train loss and the validation loss during training, to ensure that the model is not over fitting or under fitting the training data. If the train loss is much lower than the validation loss, it may indicate that the model is over fitting the training data and is not generalizing well to new data. On the other hand, if the train loss is much higher than the validation loss, it may indicate that the model is under fitting the training data and is not learning effectively.

### 4.2.1 Train loss and validation loss of Inception V3

The figure shows the Train loss and validation loss of Inception V3 of our experiment.

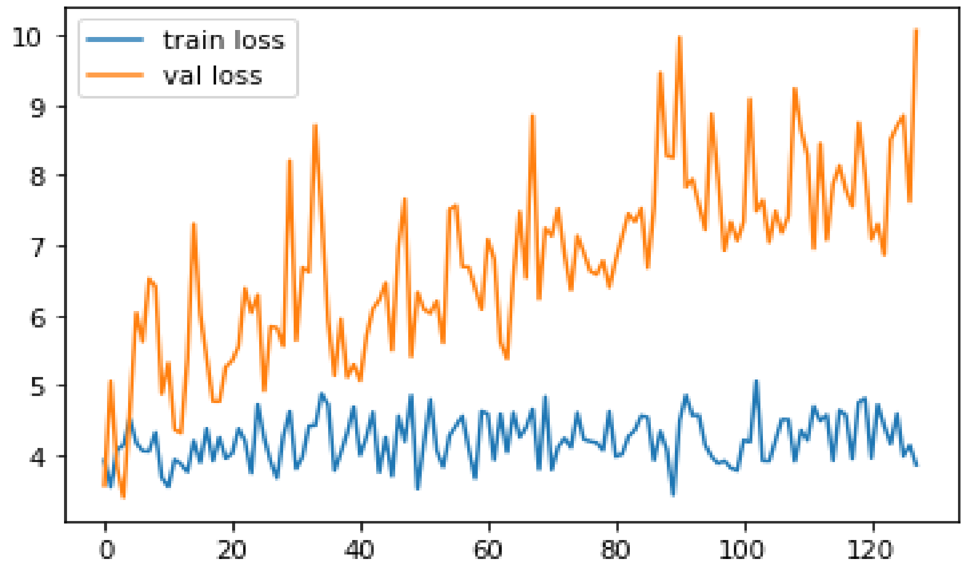



Figure 4.2.1: Train loss and validation loss of Inception V3

### 4.2.2 Train accuracy and validation accuracy of Inception V3

The figure shows the Train accuracy and validation accuracy of Inception V3 of our experiment. The accuracy of this model is 88%.

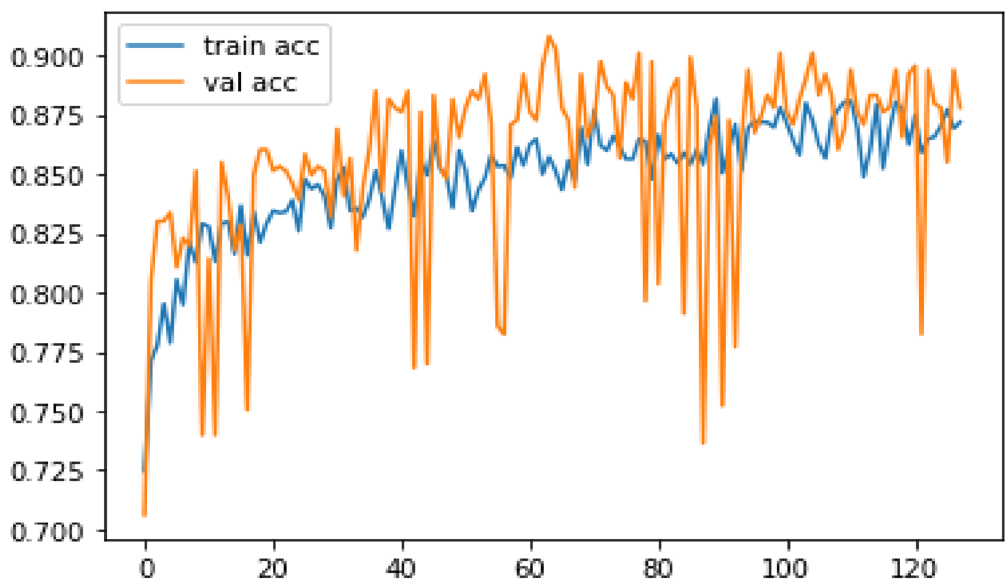



Figure 4.2.2: Train accuracy and validation accuracy of Inception V3

### 4.2.3 Classification Report of Inception V3

The table shows the Classification report of Inception V3 of our experiment.

Table 4.2.3: Classification Report of Inception V3

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| benign | 0.85 | 0.96 | 0.90 | 319 |
| malignant | 0.89 | 0.78 | 0.83 | 130 |
| normal | 0.99 | 0.75 | 0.85 | 116 |
| accuracy | | | 0.88 | 565 |
| macro avg | 0.91 | 0.83 | 0.86 | 565 |
| weighted avg | 0.89 | 0.88 | 0.88 | 565 |

### 4.2.4 Train loss and validation loss of VGG16

The figure shows the Train loss and validation loss of VGG16 of our experiment.

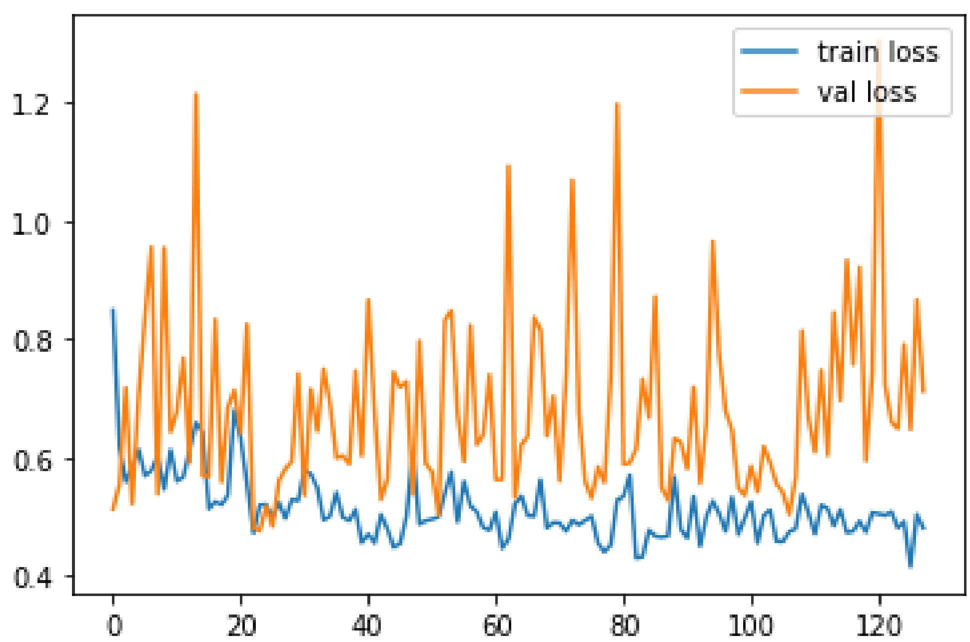



Figure 4.2.4: Train loss and validation loss of VGG16

### 4.2.5 Train accuracy and validation accuracy of VGG16:

The figure shows the Train accuracy and validation accuracy of VGG16 of our experiment. The accuracy of this model is 84%.

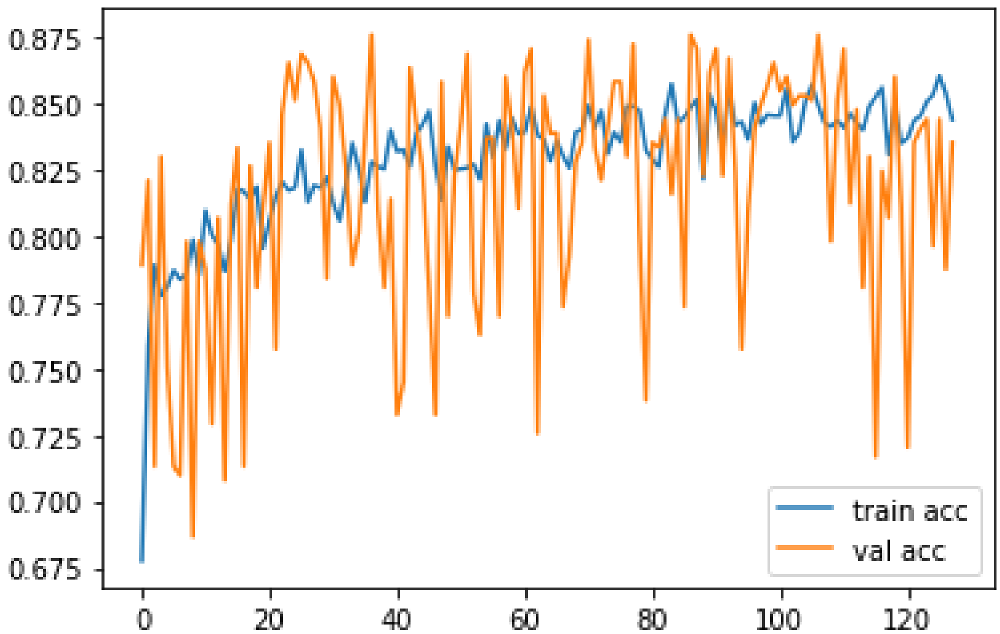



Figure 4.2.5: Train accuracy and validation accuracy of VGG16

### 4.2.6 Classification Report of VGG16:

The table shows the Classification report of VGG16 of our experiment.

Table 4.2.6: Classification report of VGG16

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| benign | 0.82 | 0.92 | 0.87 | 319 |
| malignant | 0.79 | 0.78 | 0.79 | 130 |
| normal | 0.97 | 0.67 | 0.80 | 116 |
| accuracy | | | 0.84 | 565 |
| macro avg | 0.86 | 0.79 | 0.82 | 565 |
| weighted avg | 0.85 | 0.84 | 0.83 | 565 |

### 4.2.7 Train loss and validation loss of Xception:

The figure shows the Train loss and validation loss of Xception of our experiment.

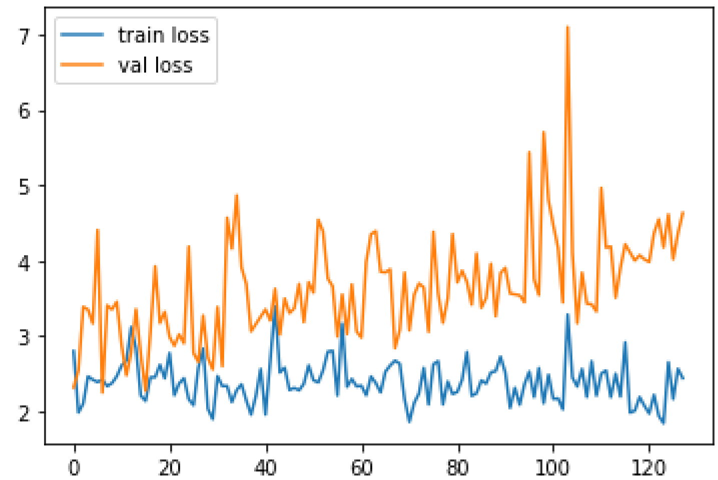



Figure 4.2.7: Train loss and validation loss of Xception

### 4.2.8 Train accuracy and validation accuracy of Xception

The figure shows the Train accuracy and validation accuracy of Xception of our experiment. The accuracy of this model is 84%.

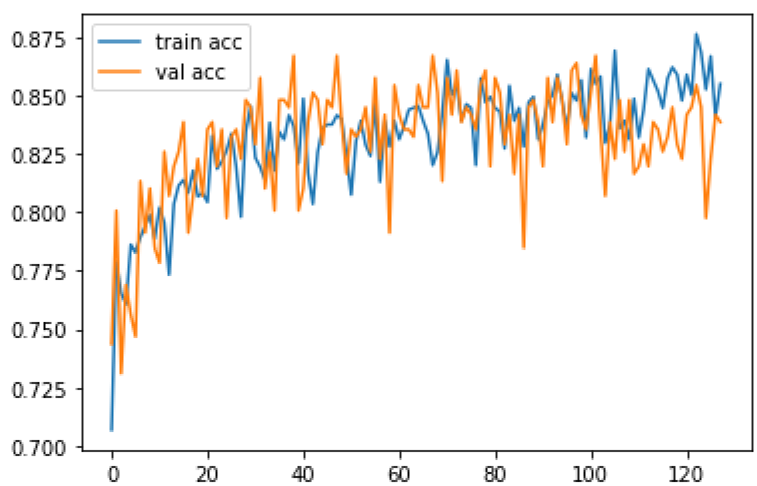



Figure 4.2.8: Train accuracy and validation accuracy of Xception

### 4.2.9 Classification Report of Xception

The table shows the Classification report of Xception of our experiment.

Table 4.2.9: Classification Report of Xception

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| benign | 0.83 | 0.93 | 0.88 | 178 |
| malignant | 0.83 | 0.77 | 0.80 | 84 |
| normal | 0.88 | 0.65 | 0.74 | 54 |
| accuracy | | | 0.84 | 316 |
| macro avg | 0.85 | 0.78 | 0.81 | 316 |
| weighted avg | 0.84 | 0.84 | 0.83 | 316 |

### 4.2.10 Train loss and validation loss of DenseNet201

The figure shows the Train loss and validation loss of DenseNet201 of our experiment.

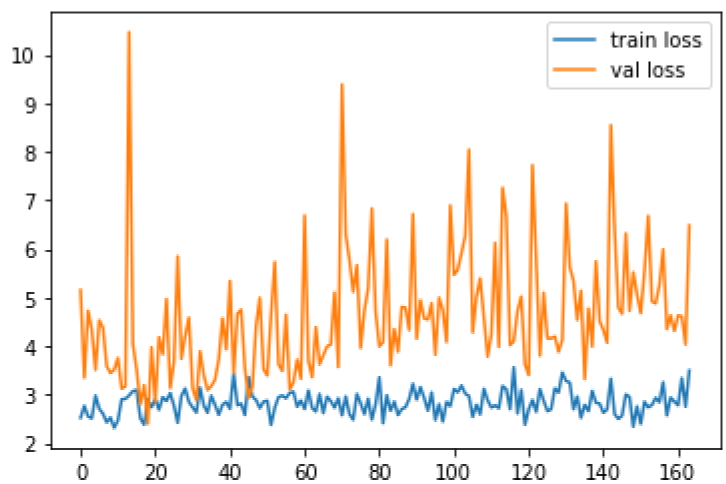



Figure 4.2.10: Train loss and validation loss of DenseNet201

### 4.2.11 Train accuracy and validation accuracy of DenseNet201

The figure shows the Train accuracy and validation accuracy of DenseNet201 of our experiment. The accuracy of this model is 80%.

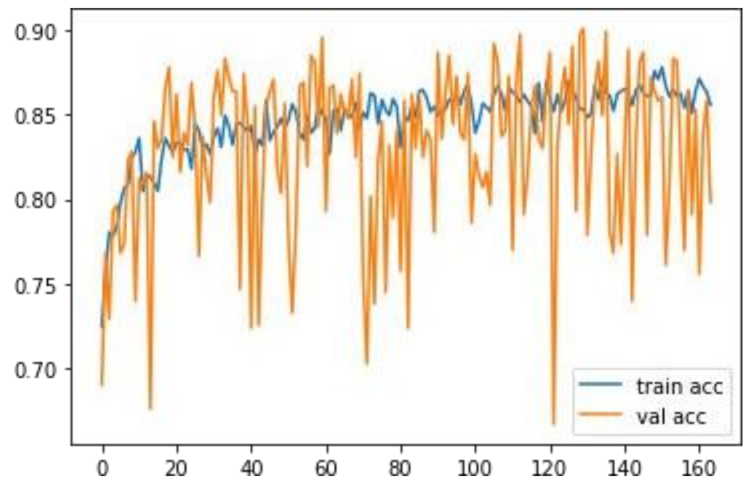



Figure 4.2.11: Train accuracy and validation accuracy of DenseNet201

### 4.2.12 Classification Report of DenseNet201

The table shows the Classification report of DenseNet201 of our experiment.

Table 4.2.9: Classification Report of DenseNet201

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| benign | 0.96 | 0.75 | 0.84 | 319 |
| malignant | 0.56 | 0.93 | 0.70 | 130 |
| normal | 0.93 | 0.79 | 0.86 | 116 |
| accuracy | | | 0.80 | 565 |
| macro avg | 0.81 | 0.82 | 0.80 | 565 |
| weighted avg | 0.86 | 0.80 | 0.81 | 565 |

## 4.3 Result Discussion & Analysis

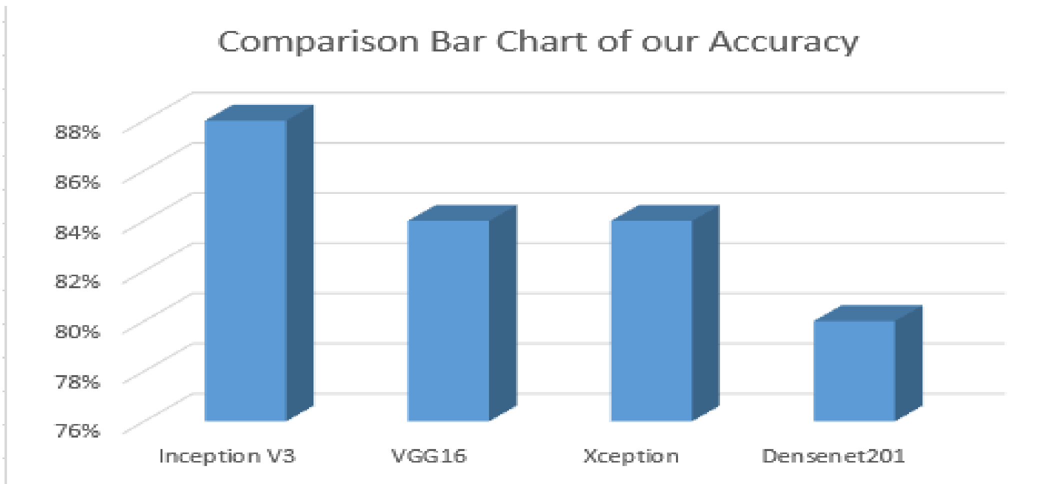
In the field of image classification, various convolutional neural network (CNN) architectures have been developed and tested. In this article, we compare the performance of four popular CNNs: Inception V3, VGG16, Xception, and Densenet201.

A comparison table of these accuracy rates is shown below:

Table 4.3: Comparison table of our Accuracy

| **Model** | **Accuracy** |
|---|---|
| Inception V3 | 88% |
| VGG16 | 84% |
| Xception | 84% |
| Densenet201 | 80% |

Based on these results, we can see that the Inception V3 model has the highest accuracy rate which is 88%, followed by VGG16, Xception, and Densenet201 with accuracy rates of 84%, 84%, and 80%, respectively. A comparison Bar chart of our accuracy rates is shown below:




In this case, the Inception V3 model has the highest accuracy but May also have higher computational requirements compared to the other models. On the other hand, Xception and VGG16 have similar accuracy rates to Inception V3 but may be more efficient in terms of computation. Ultimately, the best choice will depend on the specific requirements and constraints of the application.

**Comparison Between others papers and our paper accuracy:**

| Authors | Algorithms/Models | Dataset | Accuracy (%) | Limitations |
|---|---|---|---|---|
| S.Aminikhanghahi, S Shin, W Wang, *et al.* | Gaussian Mixture Model (GMM) | DDSM | 86 | It provides worse results when detecting benign tumors than the SVM classifier. |
| MM Saritas, A. Yasar | Artificial neural network (ANN) | Department of Obstetrics and Gynecology of the University of Coimbra (CHEA) | 86.95 | The size of the dataset used was quite small (116 instances) so might have fewer chances of being accurate in the real-world data. |
| Nanglia et al. | KNN+ SVM + DT | Private | 78% | • Less accuracy |
| Dhabvani, et al. | AlexNett+ VGG 16+ Inception+ Res net+ Nasnet | Public | 78% | • Less accuracy |
| Spanhol et al. | SVM | Private | 80% | • Less accuracy<br>• Required hand-crafted features |
| Our Work | VGG16+Xception+ Inception V3+ DenseNet201 | Public | 88% | The size of the dataset used was small |

# CHAPTER 5

# IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

## 5.1 Impact on Society

I believe my dissertation will help the environment if I explore it in the standpoint of Bangladesh. Breast Cancer affects a large percentage of Bangladeshi women, and many of them are young women. Detecting Breast Cancer at an early stage using Deep Learning could save a person's life and help to extend their lifespan in the long term. The majority of Bangladesh's populace is unconcerned about their health. I believe it will have a significant long-term impact on Bangladeshi society.

## 5.2 Ethical Aspects

My research was conducted in a perfectly ethical manner. The data I collected from the internet was only for the context of this research. More importantly, the whole effort that I have completed will benefit humanity. As a result, I do not believe this research is unethical.

## 5.3 Sustainability Plan

I had quite a protracted approach in mind while I completed my studies. Several of these plans, I believe, have been completed. I couldn't complete this research effectively the way I thought because I was almost alone in the thick of a pandemic. However, if I can solve these issuesin the future, this project will undoubtedly improve.

# CHAPTER
# CONCLUSION

## 6.1 Summary of the Study

Bangladesh has a very disproportionate incidence of breast cancer, and millennial are not exempt. The similar conclusion was reached in my research. Breast Cancer detection at an early stage is critical to a patient's ability to live a healthy life. I created a Deep Learning-based model for this purpose. Seven classic Deep Learning algorithms were employedin the model-building procedure.

## 6.2 Conclusions

An critical characteristic of my bachelor's degree program is this research. When I commenced my research, I honestly believed even less about deep learning (DL) artificial intelligence (AI) and how they are utilized in the medical and healthcare verticals. I picked up a lot of knowledge and began to like the field of AI while working on this project. Because I like evolving, I aspire to do so. I have faith that this research will be beneficial for the long term for the individuals of Bangladesh and for the fields of diabetes and deep learning.

## 6.3 Implication for Future Study

The doors have been thrown open. In the disciplines of breast cancer and deep learning,more rigorous and in-depth research is required, particularly in the perspective of Bangladesh. Even my own research has a lot of opportunity for improvement. Whilst a lot of data is demanded for deep learning to demonstrate competence, a lot of data should be gathered. A model can be developed that is far more intelligent and effective by utilizing other advanced Deep Learning algorithms and more sophisticated Ai algorithms, such as Artificial Neural Networks and Deep Learning. With more features and advanced techniques, the model can be used in manufacture.

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