FISH DISEASE DETECTION SYSTEM USING MACHINE LEARNING

BY

Sikder Rayhan Kabir
ID: 171-15-9082

AND

Kh. Abu Al Kousher
ID: 171-15-9084

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

Supervised By

Mr. Dhiman Goswami
Lecturer
Department of CSE
Daffodil International University

Co-Supervised By

Mr. Sheikh Abujar
Senior Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project titled **"FISH DISEASE DETECTION SYSTEM USING MACHINE LEARNING"**, submitted by **Sikder Rayhan Kabir**,ID No:171-15-9082 and **Kh. Abu Al Kousher**, ID No:171-15-9084 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment 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 31 January, 2020.

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Faculty of Science & Information Technology
Daffodil International University

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Department of Computer Science and Engineering
East West University

DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Mr. Dhiman Goswami, Lecturer, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Dhiman Goswami

____

Mr. Dhiman Goswami
Lecturer
Department of CSE
Daffodil International University

Co-Supervised by:

____

Mr. Sheikh Abujar
Senior Lecturer
Department of CSE
Daffodil International University

Submitted by:

Rayhan

____

Sikder Rayhan Kabir
ID: 171-15-9082
Department of CSE
Daffodil International University

Kosher

____

Kh. Abu Al Kousher
ID: 171-15-9084
Department of CSE
Daffodil International University

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ABSTRACT

Fish disease is one of the major problems in the field of fish farming in asian region. Every year farmers have to face a lot of losses in their business for the fish disease.

Especially EUS (Epizootic Ulcerative Syndrome) is one of the worst disease by which they are most commonly affected. It is very difficult for them to identify fish disease because they don't have enough knowledge about fish disease. So in this paper we actually try to help them to figure out this problem. Here we try to build a model which can automatically detect if it is a EUS disease or Non EUS disease. In earlier a few researches has been conducted to identify fish disease using machine learning but in those research there were lacking's of enough authentic data and lower accuracy. In this paper, I have proposed a machine learning approach using InceptionV3 to detect EUS and Non EUS disease with an accuracy of 95.74%. I have used total 938 images of data. Among 80% of the data used for training purpose and 20% used for testing purpose. For the experiment, I have also used some other pre-trained models for example VGG16, Xception, MobileNetV2 and InceptionRestNetV2 to find the best model for my project. Here we use data augmentation technique to enhance the images and increase the accuracy. The proposed combination of Transfer Learning and Data Augmentation techniques gives better accuracy as compared to the others.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Fish is a nutritious food and consumed by a large number of population all over the world. The major carps hold a special place among the several types of fishes. Awareness of the causes and symptoms of these diseases is very important in order to ensure proper care for fish. Epizootic ulcerative syndrome (EUS) is one of them. An infection caused by oomycete fungi known as Aphanomyces invadans is epizootic ulcerative syndrome (EUS). It is also referred to as Red Spot Disease (RSD). Since it was first recorded in 1971, it has been an epizootic disease that affects wild and farmed freshwater and estuarine finfish. Since 1971-1972 the disease gradually spread to several countries within the Asia-Pacific region. Epizootic ulcerative syndrome (EUS) has spread across the world's major continents over the last 50 years. EUS has affected more than 100 fish species, but only a few studies have verified the primary diagnostic features by demonstration. The disease is most often seen in tropical and sub-tropical waters when low temperatures and heavy rainfall occur. It mostly seen in Asian region. A very wide range of diseases and parasites can affect them when carps are in a stressed state, particularly from the poor environment and improper nutritional condition. A water mould that occurs in fresh water and estuaries in warmer waters (20°C to 30°C) causes epizootic ulcerative syndrome (EUS). This water mould binds to the fish's weakened skin, causing ulcers and destroying the tissue in the infected region. As the water mould expands, it branches into the fish's muscles and internal organs and begins to digest these tissues. Ulcerative skin lesions are common in freshwater. Lesions often signify infected or stressed aquatic conditions and can be associated with a number of pathogens, including parasites, bacteria, viruses and fungi, as well as non-infectious causes, such as toxic algae, for example. Every year farmers continue to lose profits for this disease. Totally control of EUS may not be possible in large natural water bodies. Many farmers are confused to identify EUS disease with other Non-EUS diseases.

Because it is very difficult to identify fish disease by looking at the surface of the fish. It is necessary to diagnose EUS correctly in order to prevent confusion with other ulcerative conditions. The concept of Machine learning with image processing can easily solve this problem. Using a Convolutional Neural Network (CNN), we can use deep learning that reads every pixel of an image and can extract features from an image automatically. Here we use an advance technique named ‘Transfer Learning’ which is very useful in deep learning.

1.2 Motivation

Fish play an important role in human life and considered as one of most important links in the overall food chain, it is a source of phosphorus, calcium and good fats. Because of its fast spread through the water to adjacent aqua-farms, fish disease is a serious issue. But the matter of great concern that most of the aqua-farmer do not have sound knowledge on various fish disease. Specially it is a great concern in Asia because most of the farmers in this region are uneducated. They do not know much more about fish disease. As a result they are facing a great lose every year in their business. To control and prevent the spread of the disease, rapid and accurate diagnosis is necessary. Awareness of the causes and symptoms of these diseases is very important in order to ensure proper care for fish. That is why we are going to do this work.

1.3 Objective

Our objective is to detect the disease of a fish in a very efficient way and make a system which can be useful for every aqua-farmers so that they can detect the disease and find a very simple solution of specific problem with the help of image processing. Our objective is to reduce the time of diagnosis of fish disease, reduce the cost of diagnosis and increase the production of fish.

1.4 Research Question

Diagnosing disease from fish images is extremely challenging. So many questions arise in our minds when we start our work. At that moment, we feel some questions of uncertainty.

- Which types of data should we collect for our work?
- From where we collect all of these data?
- Which platform is perfect to implement our problems?
- How people are benefited from our work?
- Is it possible to get good accuracy rate?
- How effectively we can use that?

1.5 Expected Outcome

We want to build a model that successfully helps all over the people who lost profit for fish disease. It's can able to predict almost 95% accurately for every input. We have some goals for the outcome of our project. These are given below:

- Reduce the time of diagnosis of fish disease.
- Reduce the cost of diagnosis.
- Increase the production of fish
- Correctly diagnosis all the fish disease images

1.6 Layout of the Report

Chapter one gave an introduction to the project with introduction, motivation and objective. We defined some research questions and provide some expected outcomes of our research work. We explain the whole report layout of our thesis in this section.

In chapter two we discussed about the background of our project which is covered with related works of the application and discussion of the problem and some challenges.

We are going to discuss our proposed approach theoretically in chapter three. But first of all, we mention some procedures such as data collection, data preprocessing and augmentation etc. To clear convolutional neural network concepts, we will include some photos and mathematical equations. We will explain layer of the model, test and training method.

Chapter four discusses the performance comparison of our proposed pre-trained model with some other popular transfer learning models such as MobileNetV3, VGG16, and ResNet50 etc. At last, for our proposed transfer learning model and for every model, we will complete the result discussion.

Chapter five addressed the research overview, listed some future work and conclusion of our study. We also mention some of our limitation and problems, but this chapter is closed by shown some bright future scope of this area. This chapter is actually responsible for presenting the entire project summary of our research work.

CHAPTER 2
BACKGROUND

2.1 Introduction

In computer vision and image processing, deep learning has solved issues even better than anything before. Even though there is some work being done in explaining the how deep neural networks learn, it is still black boxes. Although this field is very difficult to understand, it is a blessing for us because it solves many complex problems very easily. Thus, this project is explorative and aimed at learning how to design a neural network using Tensorflow and keras.

2.2 Related Works

The most commonly used technique in deep learning is the Convolutional Neural Network (CNN) and Image Classification. Although fish diseases are widespread, only a few related tasks are performed in image processing. Shaveta Malik, Tapas Kumar and Amiya Kumar Sahoo proposed a model (FAST-PCA_NN) that able to automatically detect or diagnoses the Fish EUS disease and they got the best accuracy of 86% [1]. In this paper the authors showed that how FAST,PCA and NN provides fish farmers and researchers with an efficient, fast and automatic tool to detect fish diseases [1]. The paper is consisting of several parts; in the first part they try to apply segmentation which helped them to enhance the image and various edge detection [1]. Features are extracted from the EUS infected fish image in the second part by feature description, i.e. HOG (Histogram of Gradient),FAST (Features from Accelerated Segment Test) and classify the image of EUS infected and non-EUS infected fish through machine learning algorithms and find the accuracy of the classification through the Classifier[1]. They show how the feature Descriptors shows good result after applying the PCA as it reduce the dimensionality reduction and gives better result [1]. But in our works we used advance image optimization technique called Data Augmentation to enhance the image and use a CNN Transfer Learning model which can able to extract feature from images very effectively.

Arshia Rehman and Saeeda Naz proposed a transfer learning architecture VGG16 to classify Brian tumors.[2]. In their proposed studies, the fine-tune VGG16 architecture achieved highest accuracy up to 98.69 in terms of classification and detection [2]. We also use VGG16 with other transfer learning algorithm in our model. For generalization of outcomes, the data augmentation methods are applied to the MRI slices to increase the samples of the dataset and reducing the risk of over-fitting [2].We also use data augmentation technique to our dataset. Ammar Adl and Neama Younan proposed a solution which can achieved accuracy of 92.8% [3]. In this paper first of all, applying Gaussian filter on images to minimize noise, then they separated background to get only object (Ichthyophthirius multifiliis parasite) by GrabCut algorithm [3]. In our model ,we use data augmentation technique to minimize noise. Then they used ORB algorithm in feature extraction that extracted some features, they extracted 4.0 features for Ich disease to make the machine learn what is or is not infected [3]. Then they used classification techniques to train and test the images and with the Logistic Regression Classifier they got high accuracy [3]. But in our thesis we use transfer learning model of CNN which can able to extract feature automatically from data. Jeong-Seon Park, Myung-Joo Oh, and Soonhee Han[4] also showed some technique to extract features from images. They got 90% as the highest accuracy applying different feature extraction method and it can classify Microscopic Images of fish disease [4]. Although huge work is done in fish detection but when it comes to fish disease detection, it is still challenging and difficult. And very few works has been done in this challenging sector but in this thesis we try to solve this challenging task by using deep learning method in a very efficient way.

2.3 Research Summary

The goal of this project is to create an image classifying Convolutional Neural Network (CNN) with the help of transfer learning for the classification of the fish image using Tensorflow and Keras, an open-source dataflow and machine learning library. A few years ago, some machine learning techniques began to be used for image-based classification. We can teach machines to understand an image by using

Convolutional Neural Networks. There are a lot of works in a different way is doing in this sector. From the background of machine learning and related work, we get better information. We come to various and many kinds of conclusions after testing, inquiring, investigating and comparing all the relevant works on fish disease detection. First of all, none of them using transfer learning which is quiet impressive specially when the dataset is very small and many of them don’t use data augmentation technique to enhance image which is comparatively good from others image enhancing technique. Secondly is accuracy rate, most of the project achieving up to 90% of the accuracy rate they claim. Now we can say there are some works on fish disease detection, but we proposed a new approach that can be able to classify fish disease more efficiently and accurately.

2.4 Scope of the Problem

There is so much area for the issue for every step of our work. It is not possible to find problems when we start a new work, but we understand that when the work progresses. Data collection part was most difficult part of our work. After data collection, before preparation, we must manipulate them in some way. And after data collection the most difficult job for working is programming syntax, model selection etc.

2.5 Challenges

We have faced several challenges to complete our project. As, this is the first time in our country we are going to identify the fish disease detection so this may called a great challenge for us to this project. Most difficult part of our project was Data collection. This is the first time in our country that we have to give much more time to collect fish images. It was more difficult for us to collect data during the pandemic. We go to Bangladesh Fisheries Research Institute (BFRI) to collect data during pandemic. It was the most challenging time. Then the big challenge to find or build a model with various layers. Define training set, avoid over fitting, select a number of epochs and batch size are more challenging for us. Similar fish image was also challenge of our project. Some fish images are same to look. It is very difficult to find the disease just look around the outside surface of the body. That time it is so tough to provide the accurate result. We are continuing our research to solve this problem. After that we need a powerful GPU to train this large number of parameters, because using a GPU it takes very few times but without a GPU it takes very long time to train a model.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

In chapter three, we are going to describe our full working procedure. We have divided our working procedure into several steps. First we discuss about collection of data and preprocessing of the data. Then we discuss how we apply Transfer Learning model of Deep Learning concept which is very latest and most popular technique for image classification. At the last part we will discuss about training and test set, input, output, every convolutional layer, implementation requirements etc. To clear the concept, we will give a proper example.

3.2 Research Subject & Instrumentation

A clear concept of our research area is given by the research subject. This project aims to identify EUS and Non-EUS type fish disease. We introduce and design our model in this section, gather perfect data, prepare and train our model, discuss results, and then apply our model to work. We choose a transfer learning model which can classify images using both Tensorflow and Keras.We also use some packages like numpy, matplotlib etc. We implement our task in Windows platform. For run this project in any platform we need some instruments. The instruments and requirements are given:

1. Python Programming Language
2. OpenCV
3. Tensorflow and KerasAPI

We choose Python because its free and easy to use and it is used for complex algorithms readability for machine learning applications. And we use "Google Colaboratory" a free online cloud-based Jupyter notebook environment and we can easily use this platform to implement out project.

3.3 Data Collection Procedure

At this time the identification of fish diseases by images is not yet a subject of extensive research so we have not found any datasets in any of the resources. Actually there is no exact dataset that exists on this subject. In this study we had to create a new authentic dataset of fish disease image. So we decided to go the Bangladesh Fisheries Research Institute (BFRI), Mymensingh to collect data. They gave us some information. However, it is not so much. So we need to collect data from other sources. We collect data from various authentic sources. We collect data from mainly three sources-

- Bangladesh Fisheries Research Institute (BFRI),Mymensingh
- "Food and Agricultural Organization of the United Nations (fao)" website
- "Shutterstock.com" website

We select many types of fish images that are found in abundance in parts of the Asian freshwater. All images are in JPG and PNG format and resolution are not same. There are almost 938 images with two categories. One is EUS fish disease other is Non-EUS fish Disease.

We have total 938 fish disease images. Among 938 images, 446 are EUS Disease images and 492 are Non-EUS Disease images. There are 200 images we collect from BFRI. Rest of the images are collected from website. It is very difficult to choose the website from which we collect information because many websites have wrong data. We always have to be aware when we collect image data. So we collect the data from authentic website which is renowned and popular all over the world. Among 938 data 80% used for training purpose and 20% used for testing purpose. Collecting those data was the first step for our thesis.

The following figure shows the raw dataset of fish disease image.

Fish Disease Name: EUS

Fish Disease Name: Non-EUS

Fish Disease Name: EUS

Fish Disease Name: Non-EUS

Fish Disease Name: EUS

Fish Disease Name: Non-EUS

Fish Disease Name: EUS

Fish Disease Name: Non-EUS

Fish Disease Name: EUS

Fish Disease Name: Non-EUS

Figure 3.1: A small part of the raw dataset

3.4 Proposed Methodology

To build the model successfully, the entire process is split into a variety of sub-processes. Figure 3.2 illustrates the entire process.

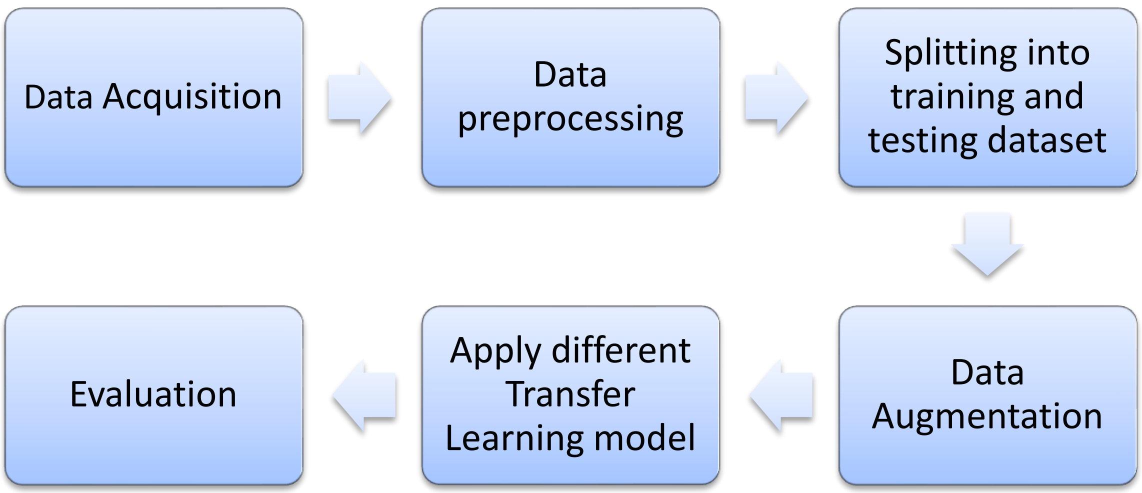


Figure 3.2: Block diagram of proposed methodology

First we have to collect the data and then we have to process the dataset because we have so many different shape and size of photos. Then we split our dataset into train and test part. Then we apply data augmentation technique to enhance our images. Then we apply many transfer learning algorithm. Here we use six types of transfer learning algorithm. These are given below:

1) VGG16
2) Xception
3) InceptionV3
4) MobileNetV2
5) InceptionResNetV2

In all of these model we apply same parameter. In all the model we use GlobalAveragePooling2D to remove unnecessary features and keep the necessary features from our images. By using this, it picks only Average value contained in the pooling window. We also use dropout to prevent overfitting on our model. Here we use 0.2 dropout value. Here we use sigmoid optimizer as it is binary classification. We set layer.trainable equal to false for freezing the layer. By setting this to false it moves all the layer's weights from trainable to non-trainable. We also use label encoder before it goes to training the model. We train all the transfer learning model using Adam optimizer and binary_crossentropy loss function to reduce loss function as possible and applied on an 80% training set and 20% test set. After applying those transfer learning algorithm we get the best result from InceptionV3. We also get the satisfactory result from other transfer learning model. Then we evaluate our model. In this following chapter we will deeply look onto the whole process from preprocessing to applying different transfer learning algorithm. In the next chapter we will demonstrate the evaluation step.

3.4.1 Data Preprocessing

First of all we collect our data. But the data was not organized. One image is different from another by size and resolution. So we need to prepare them before going for model training. The processing of data is most important for model training and better accuracy, since it reduces the cost of computing etc. We resize our image to 150x150 pixels. Then we shuffle our data to avoid over fitting our model. Then we put our data into a list of array. For normalizing our data we reduce RGB values dividing by 255. Then we use some advance technique to enhance our image data.

3.4.2 Data Augmentation

Data augmentation is a technique that can be used by creating modified model versions in the dataset to dynamically increase the size of a training dataset. To increase the quantity of data by adding slightly modified copies of existing data we used this technique. Without necessarily needing to collect new data, this method enhances the variety of data available for training models in deep learning. It makes model performance more efficient and reduces loss of classification. We use several techniques to enhance our data by using augmentation technique. These are given below:

- Rotated image in the range 40
- Zoom in the range 0.01
- width shift in the range 0.2
- height shift in the range 0.2
- horizontal flip as True

Our proposed model uses this data augmentation technique to find the best accuracy. The following figures show the images after applying data augmentation.

Figure 3.3: Rotating the image in -40 degree and +40 degree

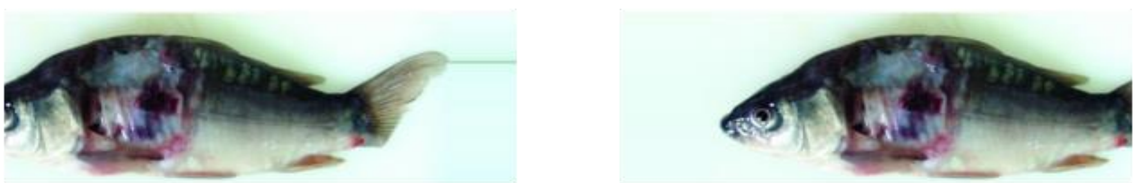


Figure 3.4: Shifting the width in the range +-0.2

Figure 3.5: Shifting the height in the range +-0.2

Figure 3.6: Horizontally flip the image

3.4.3 Convolutional Neural Network

A Convolutional Neural Network (CNN) is a deep learning algorithm that can take an input image and it can learnable weights and biases to various objects in the image and be able to distinguish one from the other. In general, CNN operations depend on inputs for pattern recognition extraction. CNN is a class of machine learning networks commonly applied to problems with image visualization, such as classification. It applies a number of convolutional filters to the input data in order to get the learning parameters for the network. Pooling layers are positioned between convolutional layers and are used to reduce the number of learning parameters used and reduce the computational require. Finally, fully connected layers set up full connections to the previous layer and after that we get the final output.

Figure 3.7 shows a basic overview of CNN architecture.

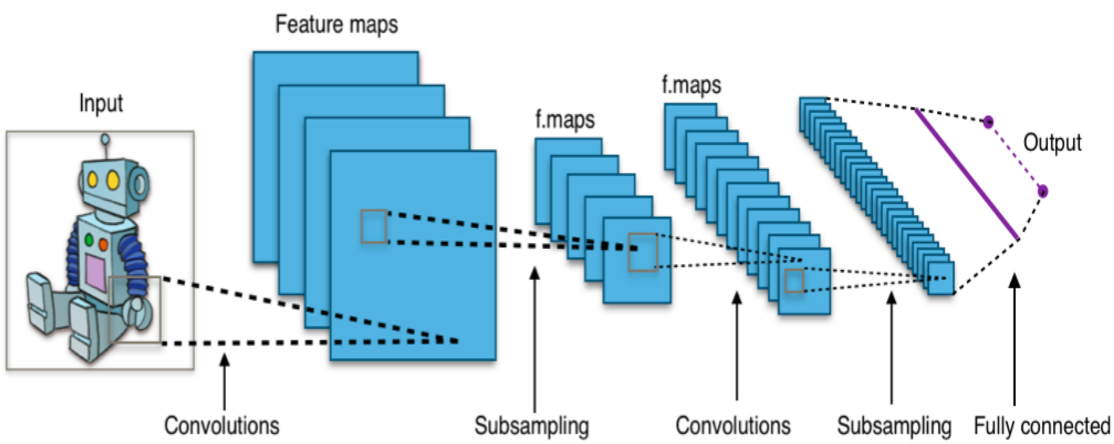


Figure 3.7: A typical CNN architecture [6]

In this project we use transfer learning algorithm to classify EUS and Non-EUS fish disease images. Transfer learning is the enhancement of learning by transfer information from a similar task that has already been learned into a new task. It is very useful because it is the reuse of pre-trained model on a new problem especially when the dataset is very small. Instead of creating a new CNN with random initialization of parameters, we follow a pre-trained CNN instead and fine-tune its parameterization for our particular domain of classification. There are many types of transfer learning are available. But here we only use six transfer learning algorithm. Here we explain the algorithm one by one.

- **VGG16:** VGG is an acronym for the Oxford University Visual Geometric Group, and VGG-16 is a 16-layer network proposed by the Visual Geometric Group [7]. VGG16 is a CNN convolution architecture which was used in 2014 to win the ILSVR (Imagenet) competition. The most amazing thing about VGG16 is that instead of making a large number of hyper-parameters, they concentrated on having 3x3 filter convolution layers with a stride 1 and the same padding and maxpooling layer of 2x2 filter of stride 2.have always been used. This network is a pretty big network and has parameters of around 138 million (approx).

  We'll discuss the architecture of the VGG-16 in detail here.

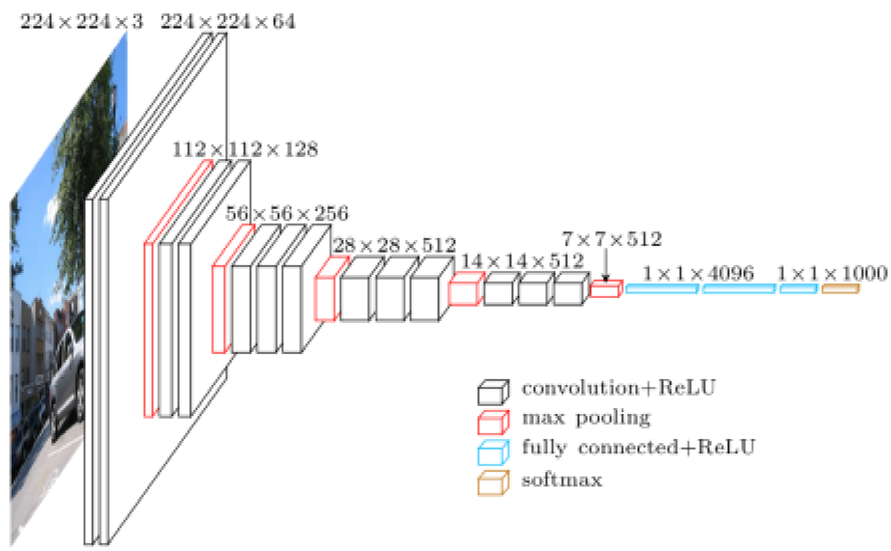


Figure 3.8: VGG16 architecture [5]

In the above diagram, all the blue rectangles and the non-linear activation function, which is a rectified linear unit, represent the convolution layers. Here we see it began with a very low channel size of 64 in this architecture, and then gradually increased by a factor of 2 after each max-pooling layer, until it reached 512. The architecture is very simple. For any number of classes, we can make this model function by modifying the last softmax dense layer unit to whatever number we want based on the classes we need to classify.

- **InceptionV3:** Inception-v3 is a convolutional architecture of the Inception family neural network that makes several improvements including the use of Label Smoothing, Factorized 7 x 7 convolutions, and used an auxiliary classifier. It is the third edition of the Inception Convolutional Neural Network from Google, originally implemented during the Challenge of ImageNet Recognition. From the original ImageNet dataset, which was trained with over 1 million training images, Inception V3 was trained using a dataset of 1,000 classes.
  We'll discuss the architecture of the InceptionV3 in detail here.

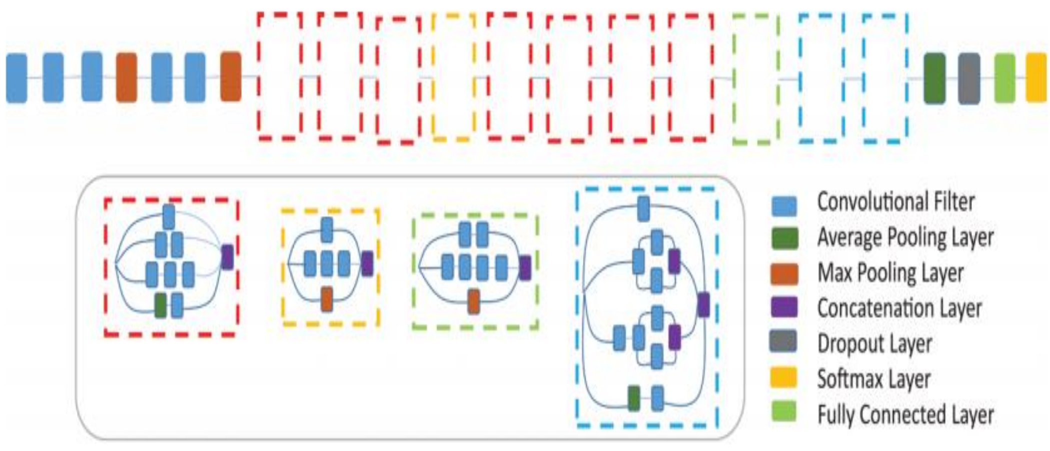


Figure 3.9: InceptionV3 architecture [8]

In the above architecture, Inception v3 network stacks 11 inception modules. Here each module consists of pooling layers and convolutional filters with rectified linear units as an activation feature [8]. This model input is two-dimensional images of 16 horizontal brain sections positioned on 4x4 grids as generated by the phase of preprocessing. The final concatenation layer is added with three fully connected layers of sizes 1024, 512, and 3. As a regularization process, a dropout with a rate of 0.6 is applied before the fully connected layers [8]. With a batch size of 8 and a learning rate of 0.0001, the model is pre-trained on the ImageNet dataset and further fine-tuned.

- **MobileNetV2:** The architecture of MobileNetV2 is based on an inverted residual structure where the residual block's input and output are thin bottleneck layers compared to conventional residual models that use extended input representations, and MobileNetV2 uses lightweight depth convolutions to filter intermediate expansion layer features [9]. This is mostly a V1 refinement that makes it even more effective and productive. In any modern environment, this module can be easily implemented using standard operations and helps our models to beat the state of the art using standard benchmarks across multiple performance points [8]. The residual link is the second new thing in MobileNetV2's building block and the residual link is used only when the number of channels entering the block is equal to the number of channels going out of it, which is not always the case as the output channels are increased every few blocks [10].
  We'll discuss the architecture of the MobileNetV2 in detail here.

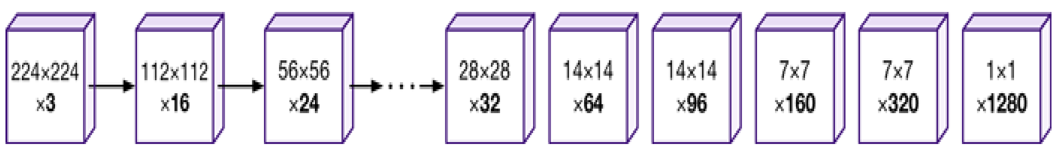


Figure 3.10: MobileNetV2 architecture [10]

In the above architecture, if we look at the data as it flows through the network, we can see how the number of channels stays fairly small between the blocks. The number of channels increases over time, as is common for this form of model but overall, thanks to the bottleneck layers which make up the connections between the blocks, the tensors remain relatively small [10]. The trick to decreasing the number of computations is to use low-dimension tensors. We won't be able to extract a whole lot of information by adding a convolutional layer to filter a low-dimensional tensor. The block architecture of MobileNet V2 provides us with the best of both worlds. MobileNetV2 offers, as we see, a very powerful mobile-oriented model that can be used as a basis for many visual recognition tasks.

- **Xception:** There are 36 convolutional layers in the Xception architecture that form the network's feature extraction foundation. The architecture of Xception has the same number of parameters so the performance improvements are not due to increased intensity, but rather to a more successful use of model parameters [11]. There is NO intermediate ReLU non-linearity in Xception, the modified depth wise separable convolution. The default size of the image for this model is 299x299.

  We'll discuss the architecture of the Xception in detail here.

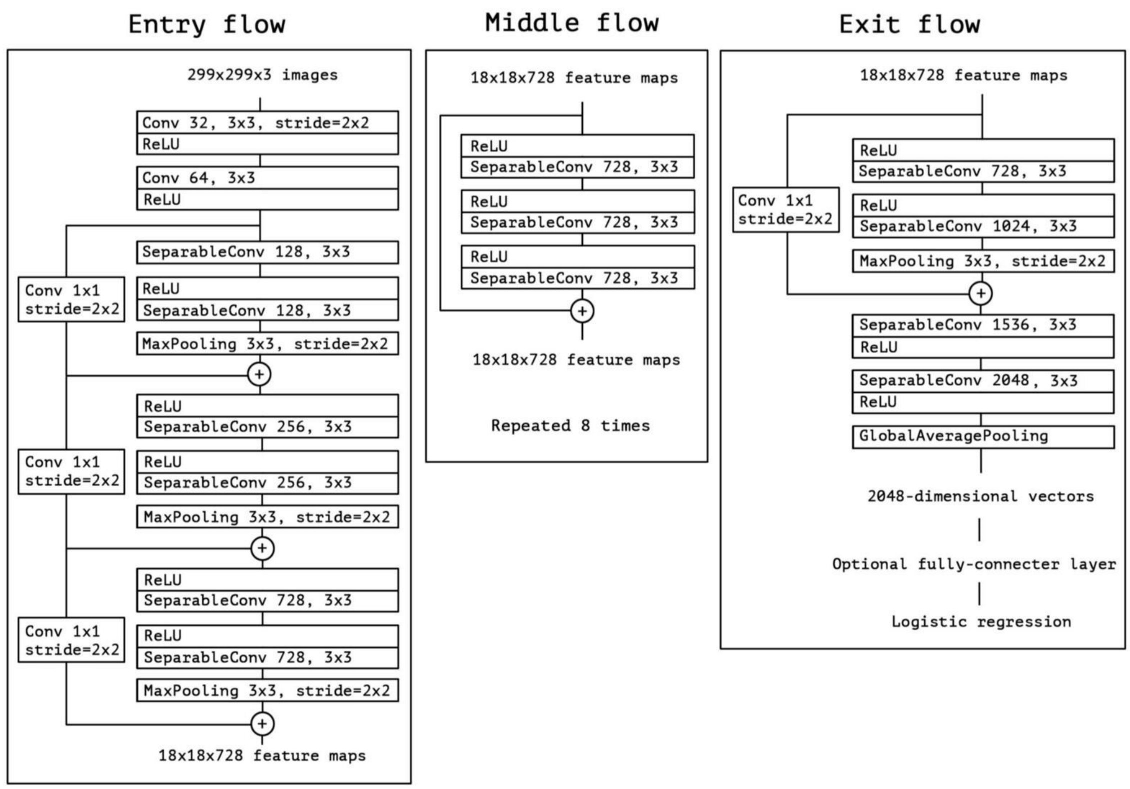


Figure 3.11: Xception architecture [11]

Here we see convolutional neural network architecture based entirely on depth wise separable convolution layers. First, the data goes through the flow of entry, then through the middle flow that is replicated eight times and finally through the flow of exit [11]. Batch normalization is accompanied by both Convolution and Separable Convolution layers which is not included in the above diagram. A depth multiplier of 1 is used for any Separable Convolution layer. The updated depth-separable convolution is SeparableConv [12]. Xception using non-residual version. From the above figure, when using residual connections, we can see that the precision is much higher [12].

- **InceptionResNetV2:** In InceptionResNetV2 the two architectures are combined by Inception-ResNet to further increase the performance. Inception-ResNet-v2 is a neural convolutional architecture that builds on the architecture family of Inception but incorporates residual ties. Residual links allow shortcuts in the model and have helped researchers to train even deeper neural networks successfully, leading to even better results. It also reduces the training time.
  We'll discuss the architecture of the InceptionResNetV2 in detail here.

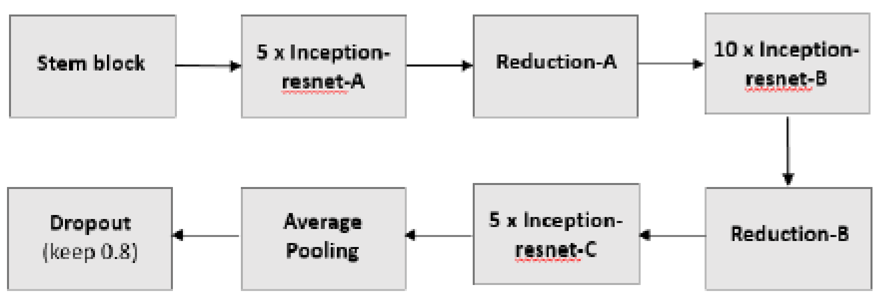


Figure 3.12: InceptionResNetV2 architecture [13]

As far as we know over 1 million images from 1k categories in ImageNet are trained on this CNN model. These deep CNN are capable of learning generic image features that are relevant to other image characteristics because it can be adopted with transfer learning technique as it trained on a very large labeled dataset. In is also known that Inception-ResNetV2 models were able to achieve higher accuracy at a lower number of epochs. Here also the input size will be 299x299. After summing up, Batch Normalization did not use here to train the model on a single GPU. The pre trained networks serve as feature extractors for generic image features in this figure, and the last two layers are fully connected for classification, layers.

3.4.4 Train the model

After generating data preprocessing and defining train and test set then we ready to train our model that consist of 80% of the total dataset. For increasing accuracy and decreasing loss as possible, we change the optimizer, learning rate, loss function, number of epoch etc. For less memory, we use 128 batch sizes and it is faster to train our model. We use 80 epochs to train our models. We also use label encoder before it goes to training. In the training step we use datagen.flow to adapt with the data augmentation. After all this set up, we started training our models.

3.5 Implementation Requirements

After our CNN methodology has been fully defined and our model has been fully trained, a required list has been developed for this image-based classification.

- Operating System (Windows 7 or above)
- Ram (Minimum 4GB)
- Hard Disk (Minimum 500GB)
- GPU (Recommended)

We should also use these developing tools:

- Python Environment
- Google colaboratory

CHAPTER 4
EXPERIMENTAL RESULTS & DISCUSSION

4.1 Introduction

We discuss our model's performance assessment in chapter 4.We also discuss about the number of parameters, accuracy level etc. Then we will compare different transfer learning models like VGG16, InceptionV3, Xception, MobileNetV2 and InceptionResNetV2. Here we use different graphs, images, confusion matrix and classification report for easy undergirding.

4.2 Experimental Setup

In order to find the best model suitable for the detection of fish diseases, different models were introduced. After implementing each model their accuracy, loss, precision, recall and f1-score were evaluated. For each of the models, the confusion matrix was plotted to visualize different model's performance. In order to find out the accuracy, precision, [14] recall and f1-score [15] the following formulas are used.

$$\text{Accuracy} = (TP+TN) / (TP+TN+FP+FN)$$

$$\text{Precision} = TP / (TP+FP)$$

$$\text{Recall} = TP / (TP+FN)$$

$$\text{F1 Score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

Where TP = True positive; FP = False positive; TN = True negative; FN = False negative. [14]

After that we use macro average and weighted average to find the average value of these models. The model with the highest accuracy was eventually selected as the optimal model.

4.3 Experimental Results & Analysis

Here Table 4.1 demonstrates a different convolutional architecture of the neural network that I used in this project with different number of total parameter, number of trainable parameter, accuracy of training, loss of training, accuracy of testing, loss of testing during the training process of the model experience.

Table 4.1: Experimental Result of different neural network model

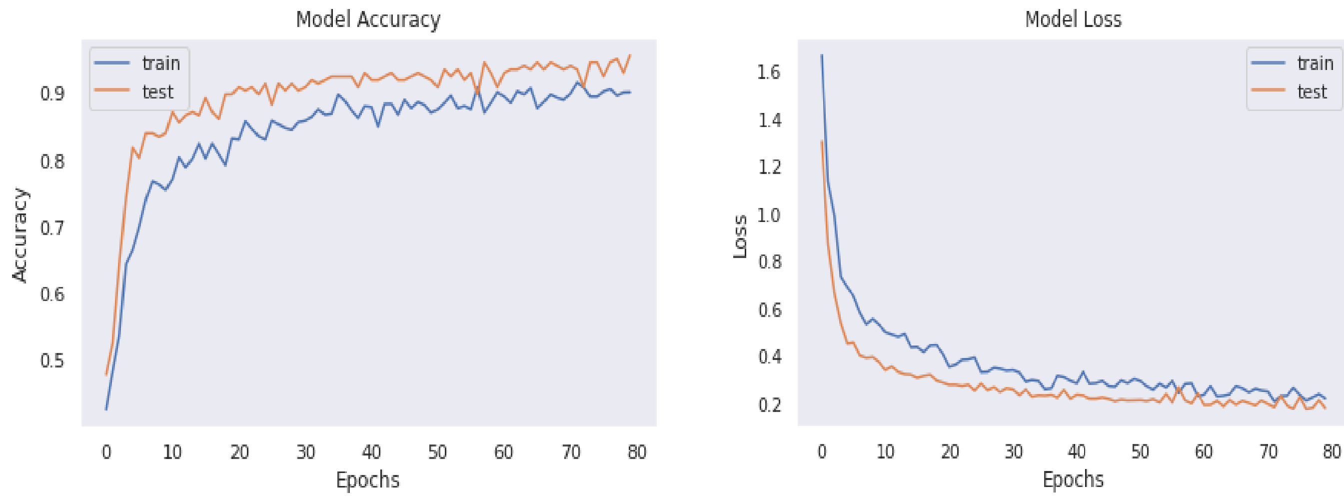
Model	Total Parameters	Trainable Parameters	Train Accuracy	Train Loss	Test Accuracy	Test Loss
InceptionV3	21804833	2049	0.9096	0.2103	0.9574	0.1819
Xception	20863529	2049	0.9114	0.2160	0.8936	0.2465
VGG16	14715201	513	0.8254	0.4399	0.8085	0.4378
MobileNetV2	2259265	1281	0.9112	0.2097	0.9043	0.2245
InceptionResNetV2	54338273	1537	0.8740	0.3203	0.8723	0.3028

Now we will discuss about graph, confusion matrix and classification report of different models we used.

- ### InceptionV3

  Inception gives us the highest accuracy and lowest loss of all the models we have used.

  Graph: figure 4.1 (a) shows the training and testing accuracy of the model and (b) shows the training and testing loss of the model.



(a) (b)

Figure: 4.1: (a) InceptionV3 model accuracy; (b)InceptionV3 model loss

Here I also shows the confusion matrix to visualize more clearly. Figure 4.2 shows the confusion matrix of the model.

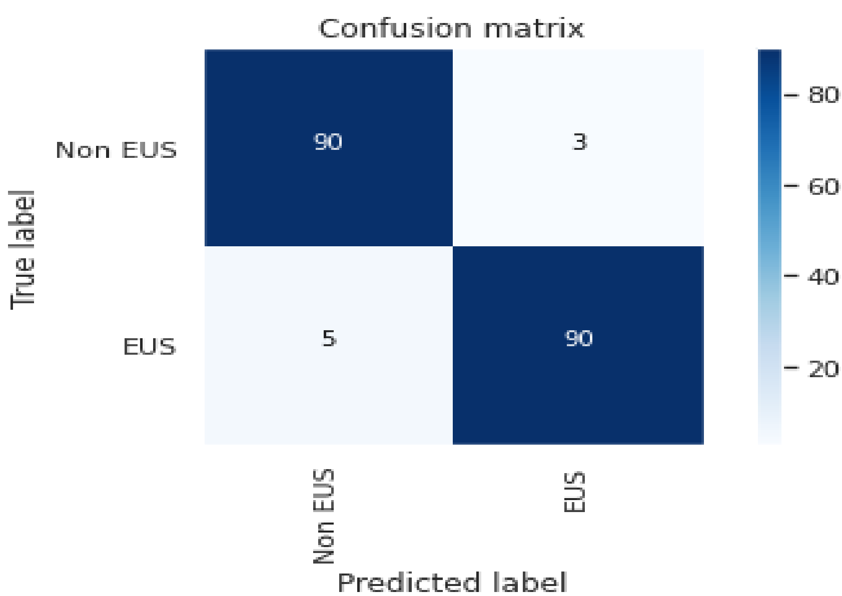


Figure: 4.2: Confusion matrix of InceptionV3 model

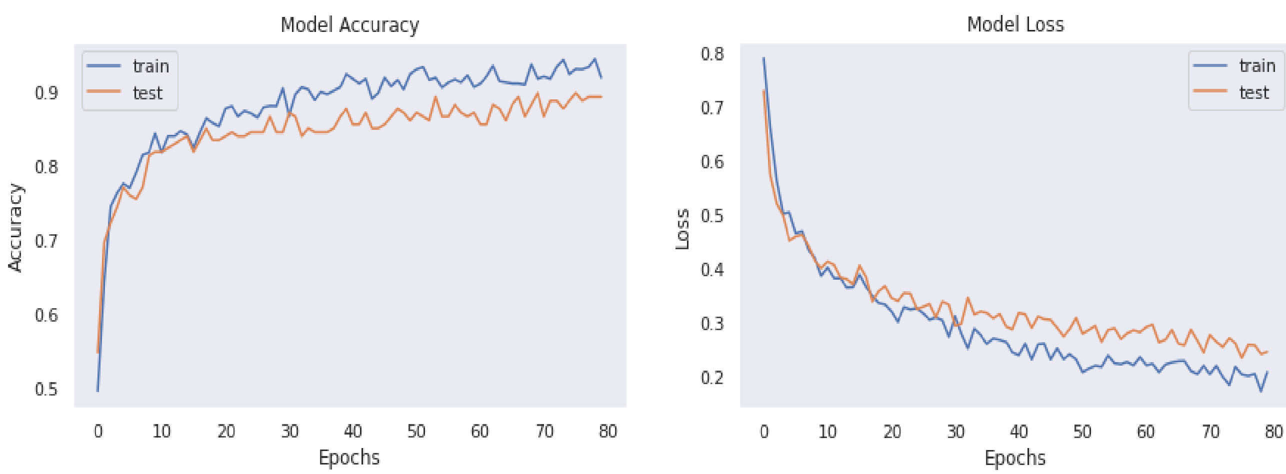
Here table 4.2 demonstrates InceptionV3 architecture of the neural network that I used in this project with precision, recall, f2-score, support etc.

Table 4.2: Classification report of InceptionV3 model

	Precision	Recall	F1- Score	Support
Non EUS	0.95	0.97	0.96	93
EUS	0.97	0.95	0.96	95
Accuracy			0.96	188
Macro avg	0.96	0.96	0.96	188
Weighted avg	0.96	0.96	0.96	188

- **Xception**

Graph: figure 4.3 (a) shows the training and testing accuracy of the model and (b) shows the training and testing loss of the model.



(a) (b)

Figure: 4.3: (a) Xception model accuracy; (b)Xception model loss

Here I also shows the confusion matrix to visualize more clearly. Figure 4.4 shows the confusion matrix of the model.

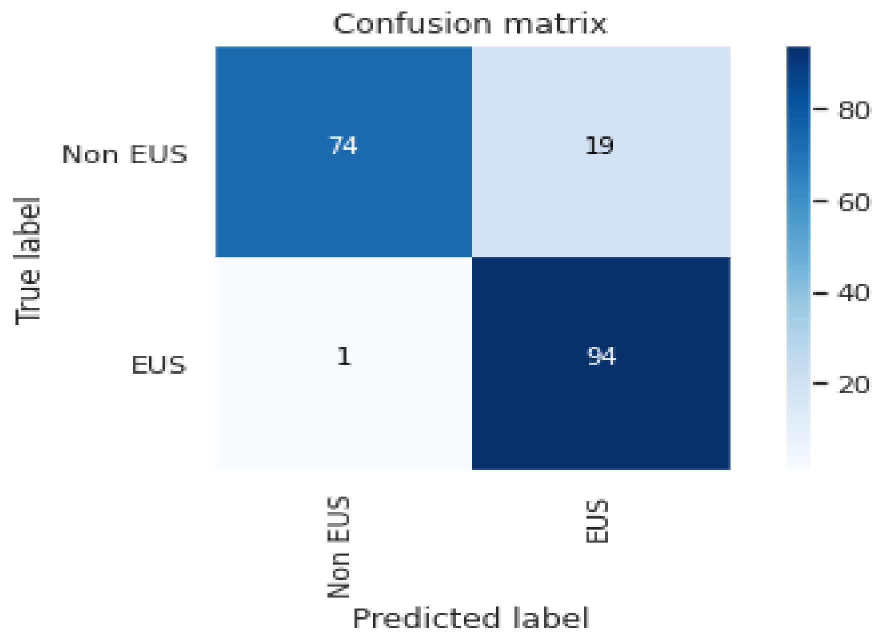


Figure: 4.4: Confusion matrix of Xception model

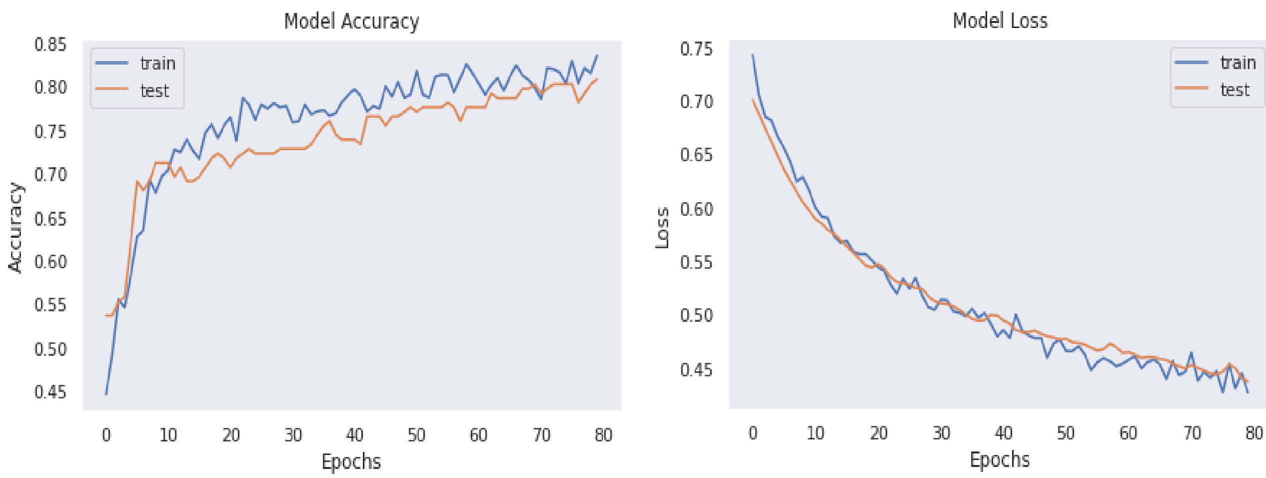
Here Table 4.3 demonstrates Xception architecture of the neural network that I used in this project with precision, recall, f2-score, support etc.

Table 4.3: Classification report of Xception model

	Precision	Recall	F1- Score	Support
Non EUS	0.99	0.80	0.88	93
EUS	0.83	0.99	0.90	95
Accuracy			0.89	188
Macro avg	0.91	0.89	0.89	188
Weighted avg	0.91	0.89	0.89	188

- **VGG16**

Graph: figure 4.5 (a) shows the training and testing accuracy of the model and (b) shows the training and testing loss of the model.



(a) (b)

Figure: 4.5: (a) VGG16 model accuracy; (b)VGG16 model loss

Figure 4.6 shows the confusion matrix of the model.

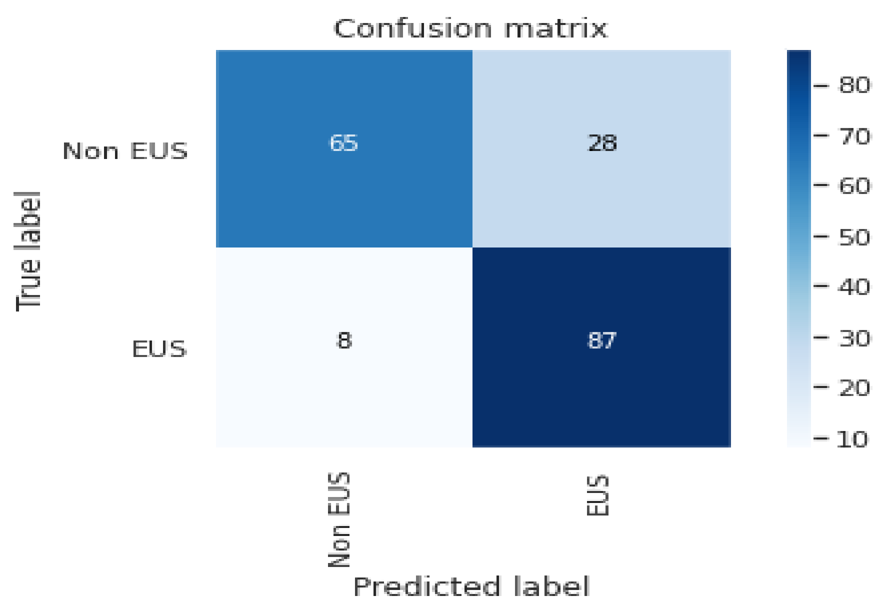


Figure: 4.6: Confusion matrix of VGG16 model

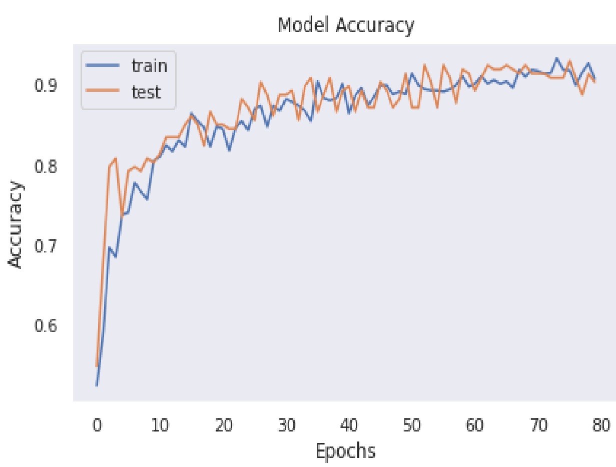
Here Table 4.4 demonstrates VGG16 architecture of the neural network that I used in this project with precision, recall, f2-score, support etc.

Table 4.4: Classification report of VGG16 model

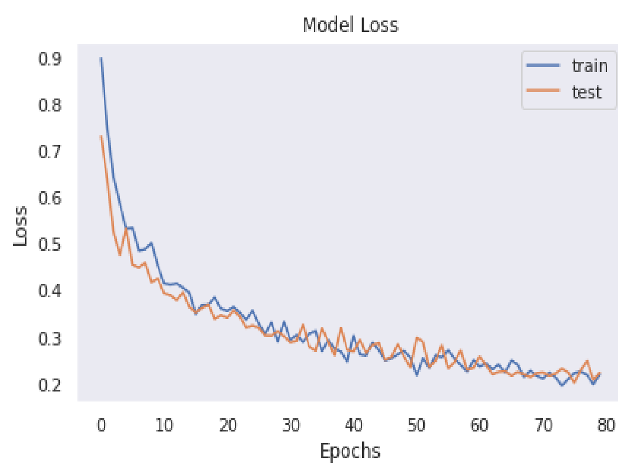
	Precision	Recall	F1- Score	Support
Non EUS	0.89	0.70	0.78	93
EUS	0.76	0.92	0.83	95
Accuracy			0.81	188
Macro avg	0.82	0.81	0.81	188
Weighted avg	0.82	0.81	0.81	188

- **MobileNetV2**

Graph: figure 4.7 (a) shows the training and testing accuracy of the model and (b) shows the training and testing loss of the model.



(a)



(b)

Figure: 4.7: (a) MobileNetV2 model accuracy; (b)MobileNetV2 model loss

Figure 4.8 shows the confusion matrix of the model.

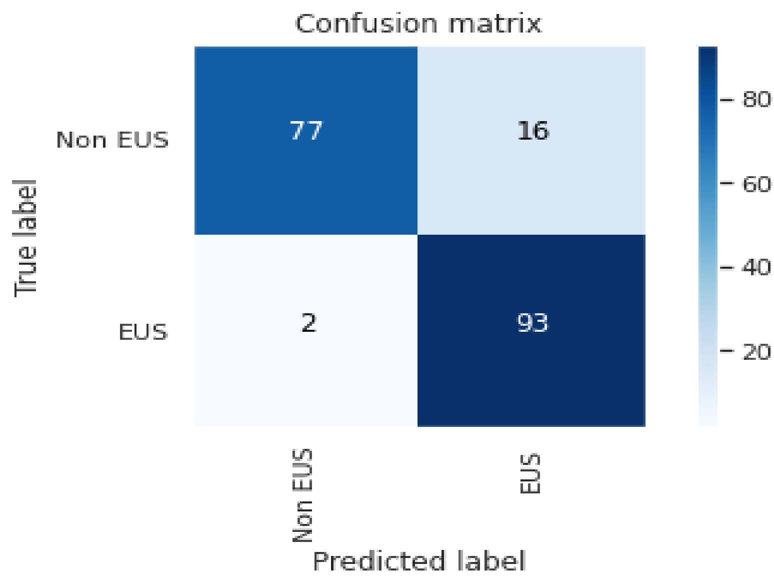


Figure: 4.8: Confusion matrix of MobileNetV2 model

Here Table 4.5 demonstrates MobileNetV2 architecture of the neural network that I used in this project with precision, recall, f2-score, support etc.

Table 4.5: Classification report of MobileNetV2 model

	Precision	**Recall**	**F1- Score**	**Support**
Non EUS	0.97	0.83	0.90	93
EUS	0.85	0.98	0.91	95
Accuracy			0.90	188
Macro avg	0.91	0.90	0.90	188
Weighted avg	0.91	0.90	0.90	188

- ## InceptionResNetV2

Graph: figure 4.9 (a) shows the training and testing accuracy of the model and (b) shows the training and testing loss of the model.

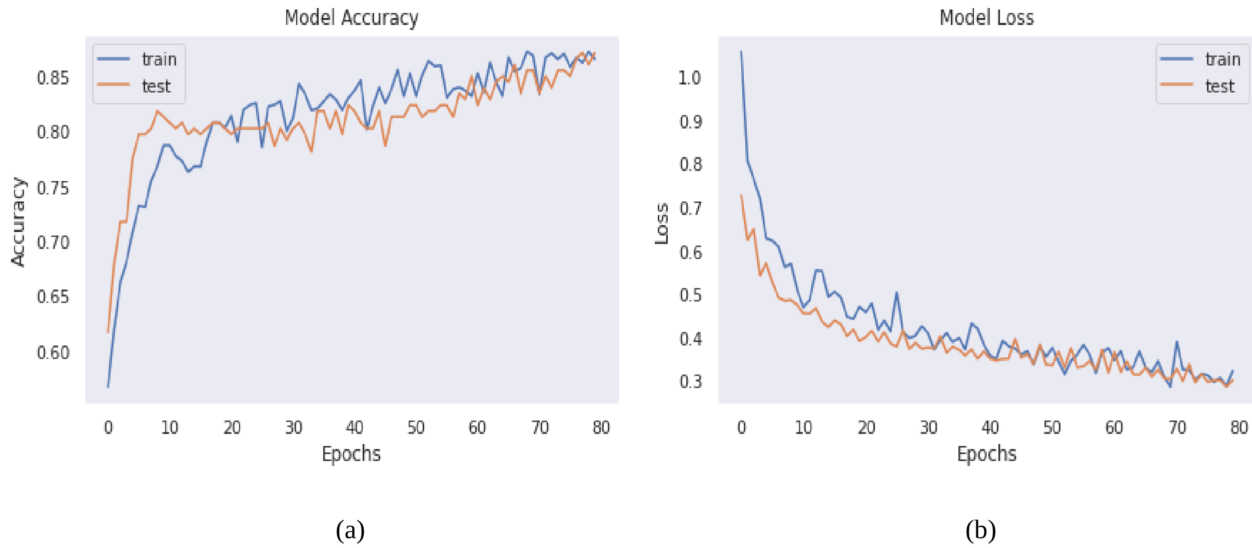


Figure: 4.9: (a) InceptionResNetV2 model accuracy; (b)InceptionResNetV2 model loss

Figure 4.10 shows the confusion matrix of the model.

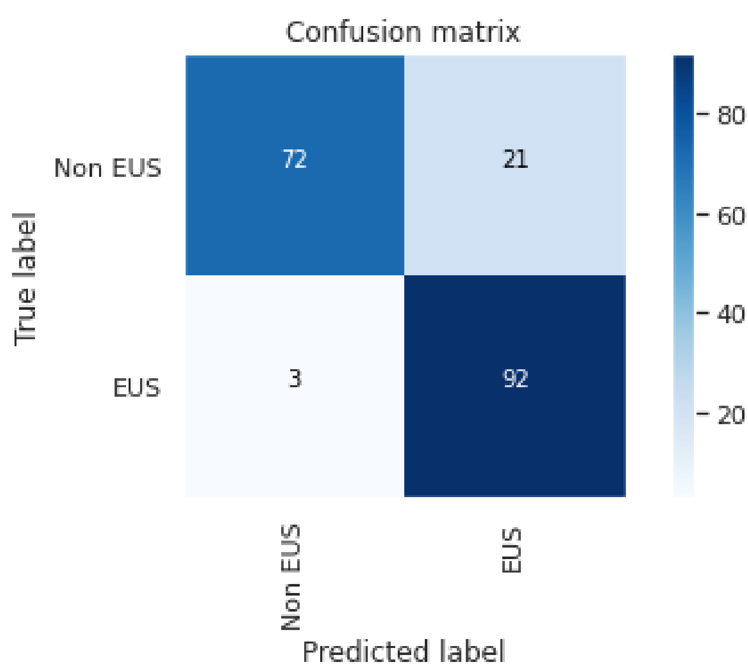


Figure: 4.10: Confusion matrix of InceptionResNetV2 model

Here Table 4.6 demonstrates InceptionResNetV2 architecture of the neural network that I used in this project with precision, recall, f2-score, support etc.

Table 4.6: Classification report of InceptionResNetV2 model

	Precision	Recall	F1- Score	Support
Non EUS	0.96	0.77	0.86	93
EUS	0.81	0.97	0.88	95
Accuracy			0.87	188
Macro avg	0.89	0.87	0.87	188
Weighted avg	0.89	0.87	0.87	188

4.4 Discussion

I have plotted a chart to determine the accuracy different architectures.

Figure 4.11 shows a chart diagram that describes the accuracy of different models.

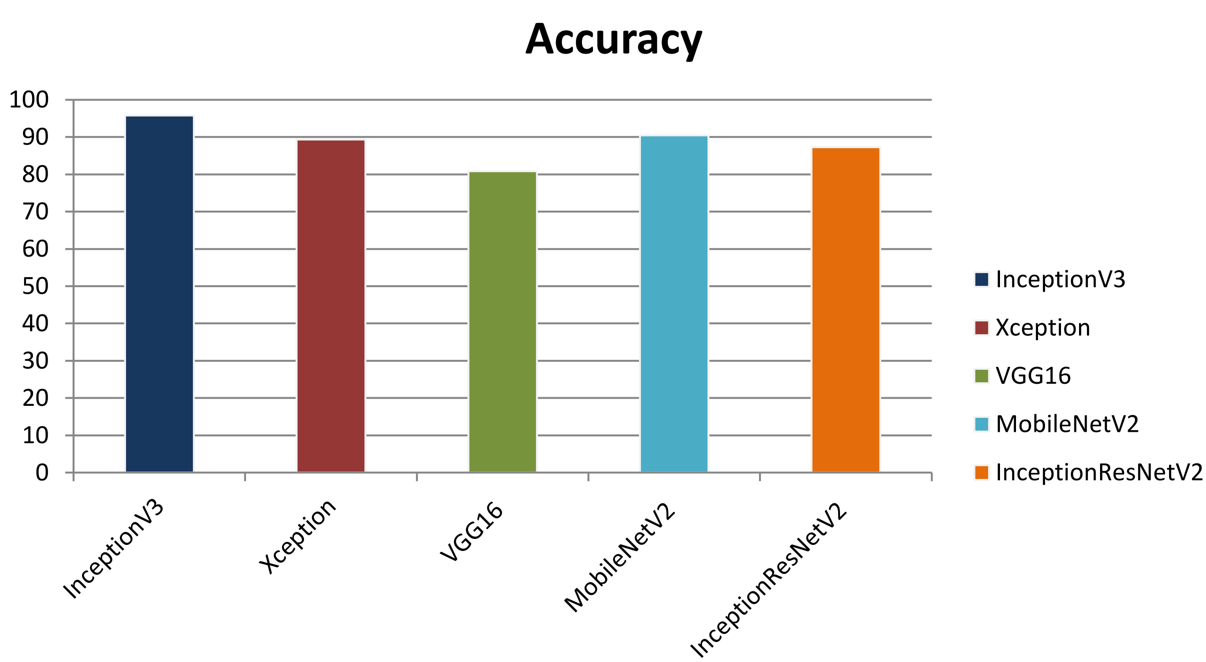


Figure 4.11: Accuracy chart diagram of different models

In the above chart we see for Inception accuracy is 95.74%, for Xception 89.36%, for VGG16 80.85%, for MobileNetV2 90.43% and InceptionResNetV2 87.23%. After comparing the accuracy of different models we can conclude that InceptionV3 generates the best accuracy. So my proposed model is InceptionV3 to identify fish disease from images.

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

We All know that in Bangladesh there are lots of people who lives their life by fish farming. They have to faces a lot of troubles regarding some common fish disease. This project is a blessing for the rural poor people for whom it is not always possible to identify fish disease. Most of the farmer in our country who cultivates fish has not any kind of knowledge about fish disease. For that reason, they have to face a lot of losses in their business. Because in the rural area there is no available expert who can help them out in this situation. So in this scenario our project can help them by identifying the fish problems and save them from a huge loss.

5.2 Impact on Environment

In today’s world, the pre requisite of doing any kind of work is that, you have to ensure that the environment will not hamper by your action. Rather is highly recommended that you should try to reduce the environment pollution. Our projects are something which will break this important policy. By using our project farmer can reduce water pollution because in most of the cases farmer don’t know the exact problem of the fish so the apply different kind of chemical which can affect the water significantly. So by our project we can make them sure about the exact problem and they can take action accordingly which will significantly reduce the uses of toxic chemicals.

5.3 Ethical Aspects

When it’s come about the ethical fact of machine learning there are some misconceptions about the test result. Which is not correct? Yes, it’s true that there is some case where you can find some issues because of the fake data they have used in their projects. But in our case we are so lucky that we can manage all the authentic data. We collect most of our data form Bangladesh Fisheries Research Institute (BFRI) which is the best place for collecting data about fish. Because they collect data for their research purpose so their data is absolutely raw and accurate. So we can confidently say that from ethical perspective there is nothing wrong about our model and project.

5.4 Sustainability Plan

The key feature or characteristic of a latest project is its sustainability. After planning and implementing the initial version of a projects the main fact that everyone should have in their mind is about the project sustainability. In case of our projects we tried our best to make our project sustainable. We are already planning to implement our model in android and iOS app in the near future. We will also try to make our projects enable for speaking in Bangla so that the people don’t know how to read and write can also use our projects. And main goal after the initial publication the want to make our model more powerful so that it can detect more disease with more accuracy.

CHAPTER 6

SUMMARY, CONCLUSION AND FUTURE WORKS

6.1 Summary of the Study

Fish disease detection is one of the most critical problems in fish farming. There is lot of ways to do this. However, most of them are poor in diagnosing fish diseases. In this project, I have used 938 fish disease images for the detection of EUS infected fish and also the healthy fish. For selecting the best machine learning model for this purpose, I have used some per-trained architecture. By comparing the performance of these models I have chosen InceptionV3 as this generates the best accuracy among the architecture I have implemented in this project.

6.2 Conclusions

In this project, I have used the dataset collected from different sources and the collected images are mostly of Asian fish so this project has created an opportunity for the people of the Asia especially for the Indian sub-continent to have to get a more correct prediction of fish disease detection. Although the proposed InceptionV3 model has generated 95.74% test accuracy and 0.1819 test loss. And we described total parameters, trainable parameters with different graph, Confusion Matrix and classification report. Our approached technique is simple but performed much faster with high accuracy from another complex model. The ultimate goal of this project is to design and optimize a CNN model to identify fish disease. To make the system more effective, we will continue our research.

6.3 Future Works

In this project, I have focused on identifying most carp fish diseases by applying various deep CNN architectures. In the future, I will focus on detecting different fish diseases. Data collection was most difficult part of our work. In the future, we will also improve the dataset and add more data. Our proposed transfer model shows better accuracy for classification against Xception, VGG16, MobileNetV2 and

InceptionResNetV2 for different fish disease detection. But in the future, there are several ways to update our model for transfer learning. We'll apply another various transfer learning models such as DenseNet, AlexNet etc. to increasing accuracy.

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