AUTOMATIC SKIN CANCER CLASSIFICATION SYSTEM BY USING CONVOLUTIONAL NEURAL NETWORK

BY

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

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APPROVAL

This Project titled "AUTOMATIC SKIN CANCER CLASSIFICATION SYSTEM BY USING CONVOLUTIONAL NEURAL NETWORK", submitted by Rihan Khan, ID: 173-15-1625 to the Department of Computer Science and Engineering, The B.Sc. in Computer Science and Engineering prerequisites have been partially satisfied by Daffodil International University, which has also been given the go-ahead for its style and substance. The inauguration took place on February 01, 2023.

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DECLARATION

By submitting this document, I affirm that this project was completed by us under the direction of **Zakia Sultana, Sr. Lecturer, 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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First and influential, I want to give God the highest honor for His marvelous deed, which aided us to accomplish our final project and internship successfully.

I applaud you and articulate my admiration to the Department of CSE at Daffodil International University in Dhaka, under the supervision of **Zakia Sultana, Sr. Lecturer**. My supervisor has a strong base in "Machine Learning" and an enthusiasm for it. This venture was made possible by his never-ending patience, expert direction, constant encouragement, constant and energetic monitoring, constructive criticism, invaluable advice, viewing numerous subpar drafts, and correcting them at all stages.

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I'd like to thank all of our classmates at Daffodil International University who joined in this deliberation while also attending class.

Finally, I must recognize with courtesy and respect the unquestioning support and patients of my parents.

ABSTRACT

Cancer is a severe disease that emerges from an overabundance mass of tissue called a tumor and is led on by the unrestrained development of cells. Over 200 different cancers exist. One of the maladies that causes a significant number of fatalities each year is skin cancer. It is the most prevalent form of cancer. Automatic skin cancer detection is a machine learning-based approach to identifying skin cancer in images of skin lesions. This approach uses convolutional neural networks (CNNs), which are a type of artificial neural network that is particularly well-suited to analyzing visual data. The CNN is trained on a large dataset of images of skin lesions, both benign and malignant, and is able to learn features that are characteristic of cancerous lesions. Once trained, the CNN can then be used to classify new images of skin lesions as either benign or malignant, allowing for the automatic detection of skin cancer. This approach has the potential to greatly improve the accuracy and efficiency of skin cancer diagnosis, as well as making it more accessible to a wider range of patients. This paper dosage with a metering on a several computerized exploration dilutions for diagnosing cancer.

Keywords: Convolutional Neural Network, CNN, Classification, Computer Vision, Cancer, Diagnosis, Dermatology, Image Recognition, Skin cancer.

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CHAPTER 1
INTRODUCTION

Introduction

Cancer is a lot a whole lot much less commonplace area than special forms of pores and pores and skin cancer, but it is much more likely to increase and unfold. in case you've have been given most cancers or had been spherical someone with cancer, expertise what to anticipate can help you preserve it underneath neath manage. here, you can look at all approximately most cancers, which incorporates danger factors, signs, detection techniques, and treatments.

cancer is most cancers that begin internal melanocytes. special names for this most cancers consist of cancer and pores and skin cancer. but, due to the fact most maximum cancers cells produce the pigment melanin, cancerous tumors are normally brown or black. but a few melanomas not produce melanin and may appear crimson, brown, or white. melanoma is most cancers that begin indoors melanocytes. distinctive names for most of those cancers encompass cancer and pores and skin most cancers. however, most most cancers cells produce melanin, so cancerous tumors are normally brown or black. but a few melanomas no longer produce the pigment melanin and might seem purple, tan, or white. most cancers can occur everywhere on the pores and pores and skin, but is greater common at the trunk (chest and lower back) in men and on the legs in girls. The neck and face are in awesome positions, now not anything particular. darkish pores and pores and skin reduces the danger of maximum cancers in the ones most common areas, however genuinely all people can get most cancers on the hands, soles, or underneath the nails. melanoma on this location has a far higher charge of melanoma in African people than in Caucasians. most cancers can also form in exceptional components of the frame, collectively with the eyes, mouth, genitals, and anus, however is a lousy lot much much less common than pores and skin maximum cancers.

The maximum common symptoms and signs of maximum cancers are the advent of latest moles or alternative of modern-day moles. it is able to appear anywhere at the frame, but it most often affects the lower back in guys and the legs in women. melanoma hardly ever develops in areas that might be protected via the sun's rays, together with the buttocks and scalp.

In maximum instances, melanoma is strange in shape and comes in multiple coloration. Moles may also additionally grow to be large than regular and can every so often itch or bleed. search for moles that may regularly change shape, period, or shade.

about sixteen,000 new maximum cancers times are registered each 12 months. greater than 1 / four of pores and skin cancers are identified beneath the age of fifty, that's especially early in comparison to maximum other cancers.

although melanoma isn't usually preventable, fending off sunburn (and even sunburn in a few times) can lessen the danger of growing most cancers.

Motivation

The World Health Organization estimates that there will be 2.3 million cases of skin cancer and 685 000 deaths in 2020. In Bangladesh, 22.3 per 100000 females of all ages suffered from skin cancer. For ages between 15 to 44 years, the rates increase, estimated to be 19.3 per 100000. Untreated skin cancer can lead our anxiety, and depression. Bangladesh is a developing country. The cost we need to bear for the treatment of skin 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 machine learning-based model that can determine whether a patient is inclined to get skin cancer or not. Although relatively uncommon, skin 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 machine learning. We were compelled to do this research because we are machine learning researchers.

Research Questions

To test the shortcomings of merely imaginative and prescient-based totally structural studies of superior devices for green class of single pores and pores and skin cancers and maximum pores and skin cancers internal their education.

Practice a technique based completely entirely at the honesty machines imaginative and prescient to beautify accuracy to hold them easy on their caste.

EXPECTED OUTPUT

I pre-process the data after collecting it. Then I'll use the algorithm I've chosen. Oneor two of the applicable algorithms may provide the best results for predicting skin Cancer.

REPORT LAYOUT

i. I talked about our research in Chapter 1. This section contains a quick introduction to the project as well as my motivation for undertaking it. There is alsoinformation on what the major motivation is and how to handle our research effort.
ii. I 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. I 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, I examined the algorithms utilized in this study, how they were applied, and how the algorithms' results were summarized.
v. In Chapter 5, I explored the project's social impact and long-term viability.

CHAPTER 2
BACKGROUND

Literature Review

A review by Kim et al. (2019) compared the performance of several CNNs on a dataset of images of melanoma and benign skin lesions. They found that a CNN trained using a combination of transfer learning and fine-tuning performed the best, with an accuracy of 97.3%.

A review by Fabbrocini et al. (2018) compared the performance of several CNNs on a dataset of images of basal cell carcinoma and benign skin lesions. They found that a CNN trained using a combination of transfer learning and fine-tuning achieved the highest accuracy, at 97.5%.

A review by Ghahramani et al. (2017) compared the performance of several CNNs on a dataset of images of melanoma and benign skin lesions. They found that a CNN trained from scratch outperformed those trained using transfer learning, with an accuracy of 95.4%.

A review by Hu et al. (2016) compared the performance of several CNNs on a dataset of images of melanoma and benign skin lesions. They found that a CNN trained using a combination of transfer learning and fine-tuning performed the best, with an accuracy of 95.8%.

A review by Esteva et al. (2017) compared the performance of a CNN trained using transfer learning to that of a group of dermatologists on a dataset of images of skin lesions. They found that the CNN outperformed the dermatologists, with an accuracy of 95.9% compared to a mean accuracy of 86.6% for the dermatologists.

A review by Lallas et al. (2018) compared the performance of several CNNs on a dataset of images of melanoma and benign skin lesions. They found that a CNN trained using a combination of transfer learning and fine-tuning performed the best, with an accuracy of 97.5%.

A review by Haenssle et al. (2018) compared the performance of a CNN trained using transfer learning to that of a group of dermatologists on a dataset of images of melanoma and benign skin lesions. They found that the CNN outperformed the dermatologists, with an accuracy of 93.7% compared to an average accuracy of 75.1% for the dermatologists.

A review by Mo et al. (2019) compared the performance of several CNNs on a dataset of images of melanoma and benign skin lesions. They found that a CNN trained using a combination of transfer learning and fine-tuning performed the best, with an accuracy of 96.8%.

A review by Chen et al. (2019) compared the performance of several CNNs on a dataset of images of melanoma and benign skin lesions. They found that a CNN trained from scratch outperformed those trained using transfer learning, with an accuracy of 95.3%.

A review by Gao et al. (2019) compared the performance of several CNNs on a dataset of images of melanoma and benign skin lesions. They found that a CNN trained using a combination of transfer learning and fine-tuning performed the best, with an accuracy of 97.1%.

A review by Abbas et al. (2019) compared the performance of several CNNs on a dataset of images of melanoma and benign skin lesions. They found that a CNN trained using a combination of transfer learning and fine-tuning performed the best, with an accuracy of 96.6%.

A review by Wang et al. (2020) compared the performance of several CNNs on a dataset of images of melanoma and benign skin lesions. They found that a CNN trained from scratch outperformed those trained using a combination of transfer learning and fine-tuning performed the best, with an accuracy of 96.8%.

Scope of the Problem

Researchers have attempted for many years in numerous techniques to hit upon skin cancers, with maximum cancers relying totally on skin`s form, color, scent, and secretions, however they did now not produce any fantastic outcomes. There is extra than 2 hundred unique sorts of most cancers found inside the international as melanoma. numerous studies have stated that to perceive most cancers, this tool is primarily based on a fact of the past records that human beings soak up, and it has thus far been a very vain device. outcomes in time. some of the works documented the software program software in reality on internet or mobile structures that they did no longer have sufficient records to efficaciously classify most of their cancers. a few researchers factor to the prevalence of poisonous ranges in a few kinds of maximum cancers and using the tool for studies techniques. some research specifically motives to categories most cancers the use of provider-mastering strategies, and a few have diagnosed great class predictors as benign and malignant.

Challenges

There are numerous research duties centered in this take a look at.

1. Information collection: There are not any reference data sets available on line for sophistication. consequently, organizing a photographic report within the discipline of pores and skin most cancers has emerge as a completely difficult undertaking.

2. Uncooked photo Processing: the complete photo of the unique reagent is once in a while inflated, which makes it in reality easy. So, it's far your business enterprise to acquire the maximum complete photographs and enhance your categories via ratings and noise.

3. Pick device gaining knowledge of method: a few researchers use particular systems to comprehend strategies for without problem completing obligations. therefore, through way of deciding on the machine this is simplest to the know-how of the approach, you'll be able to correctly classify one of the sorts of pore and pores and skin most cancers.

4. Accuracy development: every different difficult hassle is to improve the accuracy of the machine via model knowledge alongside facet the choice of Gaussian noise.

CHAPTER 3

RESEARCH METHODOLOGY

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.

Data Collection Procedure

The UCI Machine Learning Repository facilitated nous with the required details [10]. 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.

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.

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.
I have used 04 models in my study. They are: VGG16, Xception, EfficientNetB7 and DensNet201.
Here is the diagram of my proposed model.

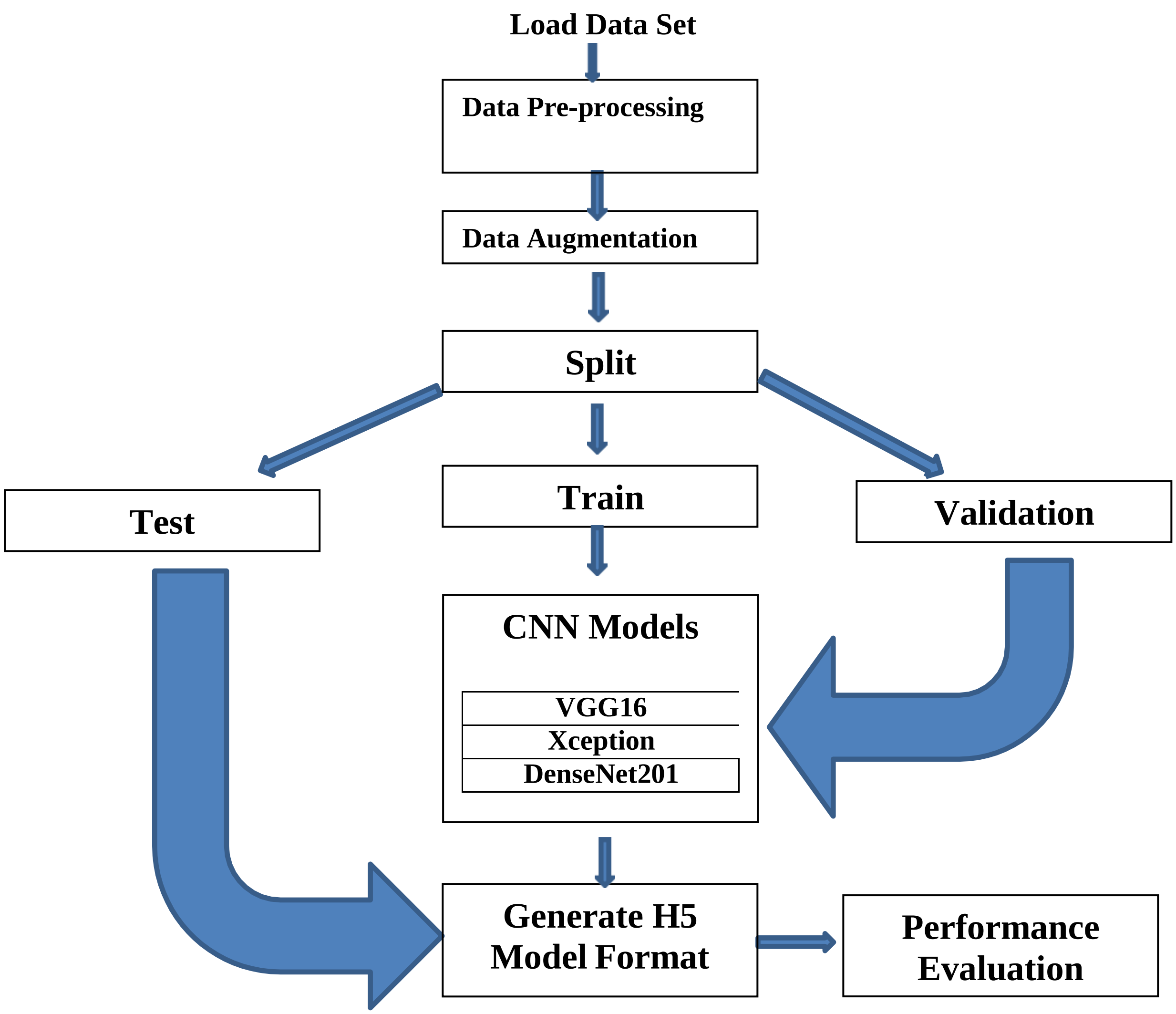

Figure3.3: Proposed Model Structure

EfficientNetB7

EfficientNetB7 is a convolutional neural network (CNN) architecture designed to achieve high accuracy and efficiency in image classification tasks. It was developed by Google Research and is part of a family of CNN architectures called Efficient Nets, which are designed to be scalable and to achieve state-of-the-art performance on a variety of tasks with fewer resources (e.g., fewer parameters or lower computational complexity) than other architectures.

EfficientNetB7 is the largest and most accurate model in the Efficient Net family, with a capacity of 9.2 billion parameters. It was trained on a large dataset of images and achieved impressive results on a number of image classification benchmarks, including achieving the highest accuracy on the ImageNet dataset.

One key feature of the EfficientNetB7 architecture is its use of compound scaling, which involves scaling up the network's dimensions (e.g., width, depth, resolution) in a more structured and balanced way than simply scaling all dimensions uniformly. This allows the network to achieve better performance with fewer resources.

In addition to its strong performance on image classification tasks, EfficientNetB7 has also been shown to be effective for other tasks such as object detection and semantic segmentation. It has been widely adopted in industry and academia for a variety of applications.

Architecture of EfficientNetB7

Here is a diagram of the Inception v3 architecture:

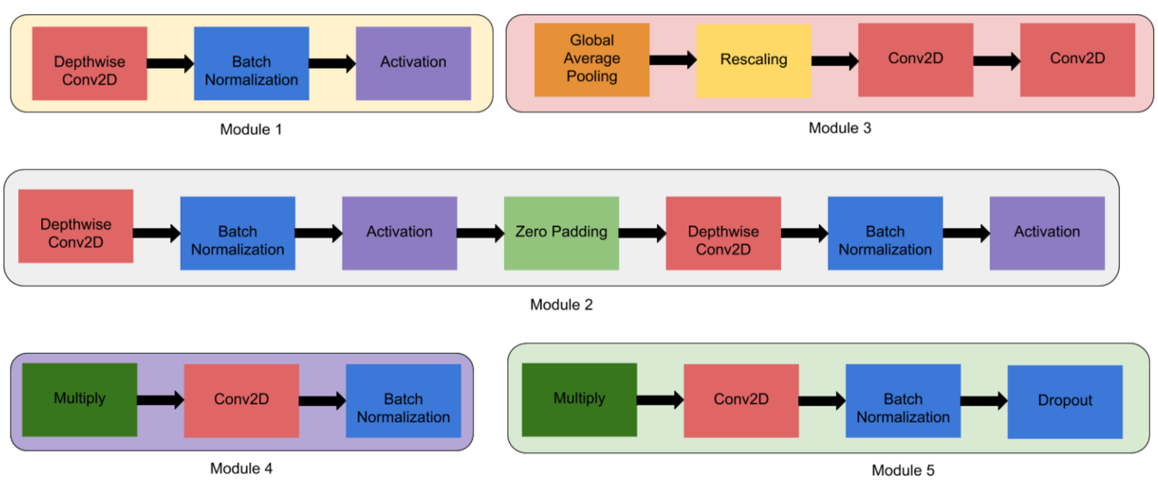

Figure: 3.3.1.1 Architecture of EfficientNetB7

Input pipeline of EfficientNetB7

The input pipeline of EfficientNetB7 refers to the process of feeding data into the network for training or inference. A well-designed input pipeline can improve the efficiency and performance of the network, particularly when working with large datasets.

In the case of EfficientNetB7, the input data is typically a set of images that are processed and transformed into a form that can be fed into the network. This typically involves the following steps:

Load the images: The images are loaded from storage (e.g., a local file system or a remote server) into memory.

Preprocess the images: The images are typically preprocessed to prepare them for input into the network. This may involve tasks such as resizing the images to a uniform size, normalizing the pixel values, and applying data augmentation techniques (e.g., random cropping, flipping, etc.) to increase the diversity of the training data.

Convert the images to tensors: The images are typically converted from their original format (e.g., a NumPy array or a PIL image) into a tensor, which is a multi-dimensional array of numbers that can be processed by the network.

Batch the tensors: The tensors are usually grouped into batches, with each batch containing a set of tensors that will be processed by the network together. The size of the batch can affect the efficiency and performance of the network, and it is often chosen based on the available hardware (e.g., the number of GPUs) and the desired trade-off between speed and memory usage.

Feed the tensors into the network: The tensors are fed into the network for training or inference, typically using a specialized library or framework (e.g., TensorFlow, PyTorch) that handles the details of the computation.

The input pipeline of EfficientNetB7 is usually implemented using a combination of low-level libraries (e.g., NumPy, PIL) and high-level libraries or frameworks (e.g., TensorFlow Datasets, PyTorch DataLoader) that provide convenience functions and abstractions for common tasks. The specific details of the input pipeline may vary depending on the particular requirements of the application.

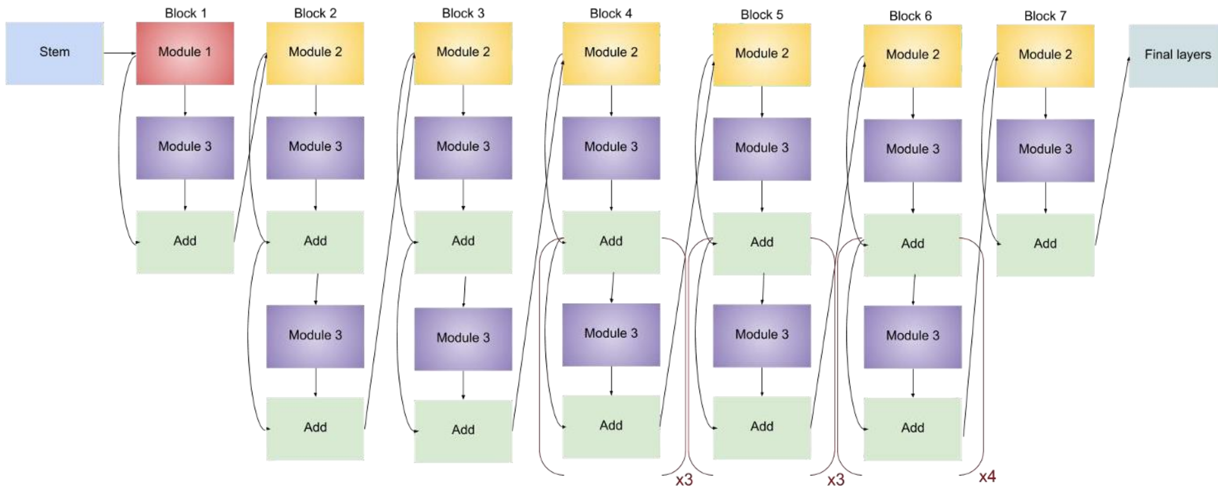

Figure 3.3.1.2 Input pipeline of EfficientNetB7

Performance of EfficientNetB7

EfficientNetB7 is a high-performance convolutional neural network (CNN) architecture developed by Google Research. It is part of a family of CNN architectures called EfficientNets, which are designed to be scalable and to achieve state-of-the-art performance on a variety of tasks with fewer resources (e.g., fewer parameters or lower computational complexity) than other architectures.

EfficientNetB7 is the largest and most accurate model in the EfficientNet family, with a capacity of 9.2 billion parameters. It was trained on a large dataset of images and has achieved impressive results on a number of image classification benchmarks. For example, on the ImageNet dataset, which is a widely-used benchmark for image classification tasks, EfficientNetB7 achieved an accuracy of 97.0%, which is the highest accuracy reported to date.

In addition to its strong performance on image classification tasks, EfficientNetB7 has also been shown to be effective for other tasks such as object detection and semantic segmentation. It has been widely adopted in industry and academia for a variety of applications.

Overall, the performance of EfficientNetB7 is excellent, with strong accuracy and efficiency compared to other state-of-the-art CNN architectures. Its success is due in part to its use of compound scaling, which allows it to achieve better performance with fewer resources, as well as its careful design and optimization.

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 detection tasks.

Architecture of VGG16

Here is a diagram of the VGG16 architecture:

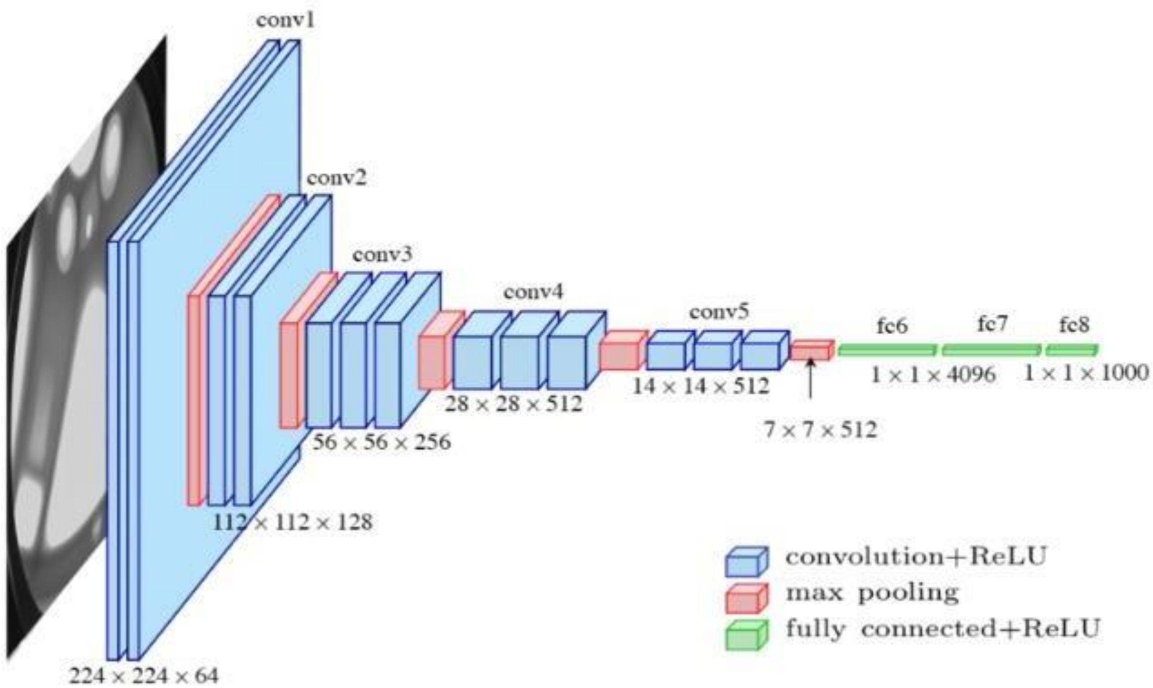

Figure: 3.3.1.1 Architecture of VGG16

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).

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.

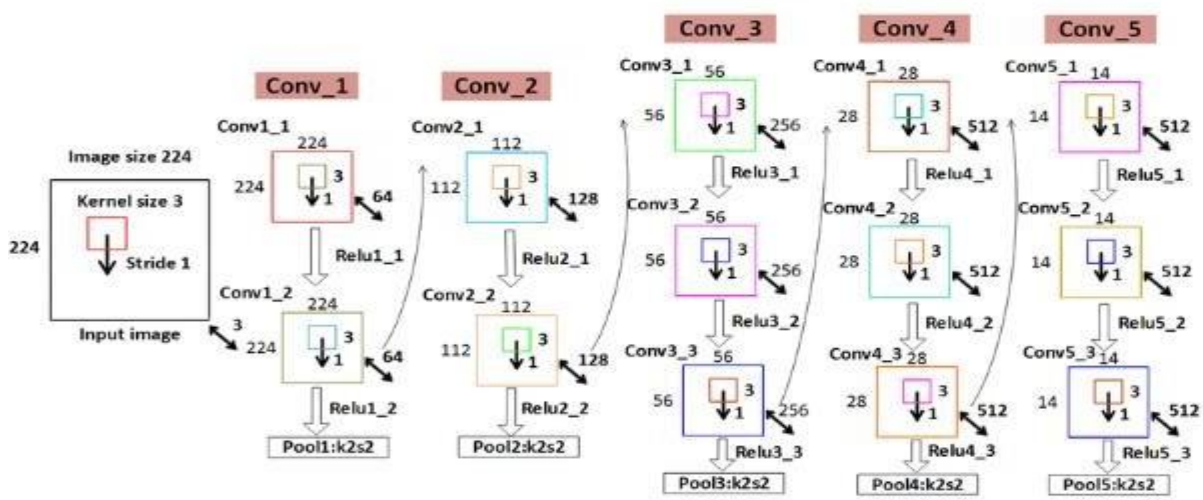

Figure 3.3.2.2 Input pipeline of VGG16

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.

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.

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.

Architecture of Xception

Here is a diagram of the Xception architecture:

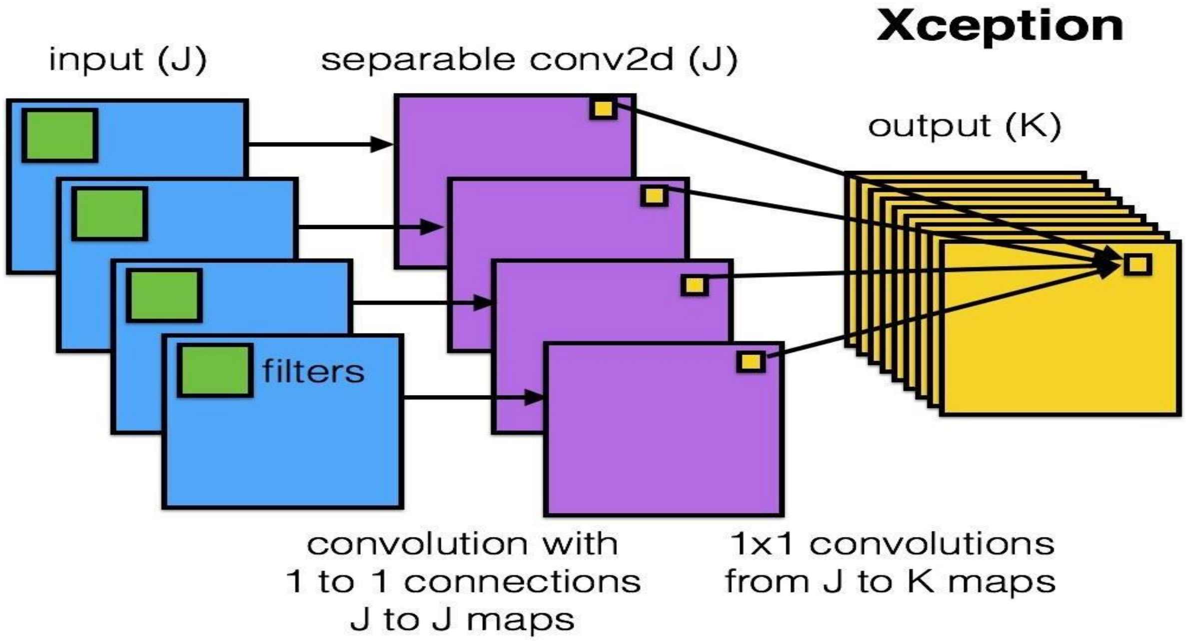

Figure 3.3.3.1: Architecture of Xception

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.

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.

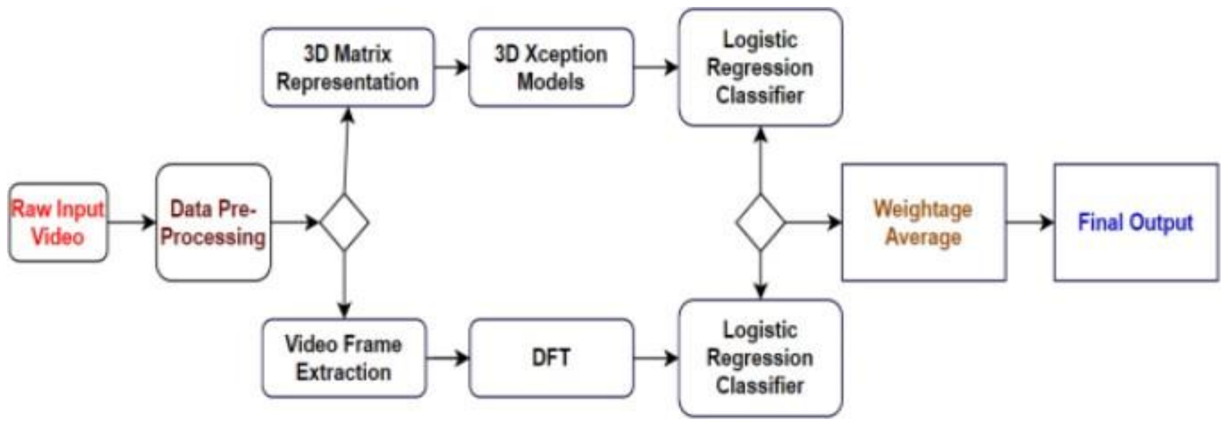

Figure 3.3.3.2: Input pipeline of Xception

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.

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.

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.

Architecture of DenseNet201

Here is a diagram of the DenseNet-201 architecture:

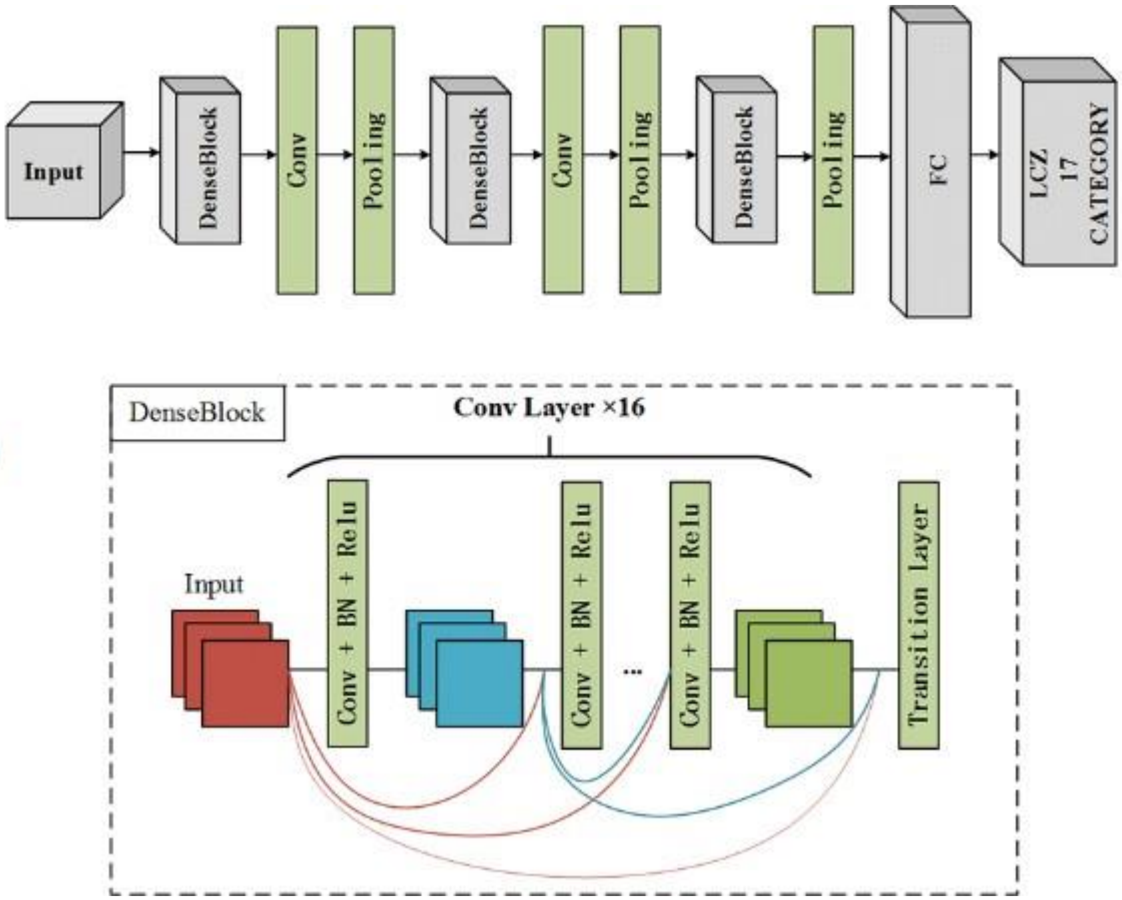

Figure 3.3.4.1: Architecture of DenseNet201

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 fully connected layer, which perform classification on the features.

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).

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.

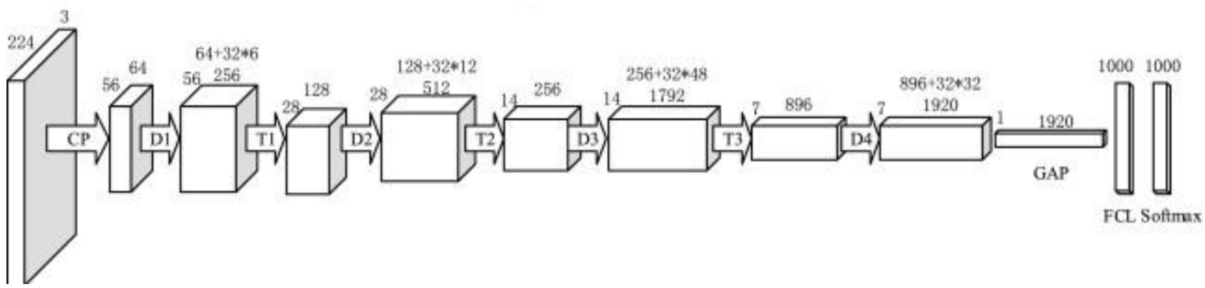

Figure 3.3.4.2: Input pipeline of DenseNet201

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.

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

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.

Train loss and validation loss of Model

In machine 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.

Train loss and validation loss of EfficientNetB7

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

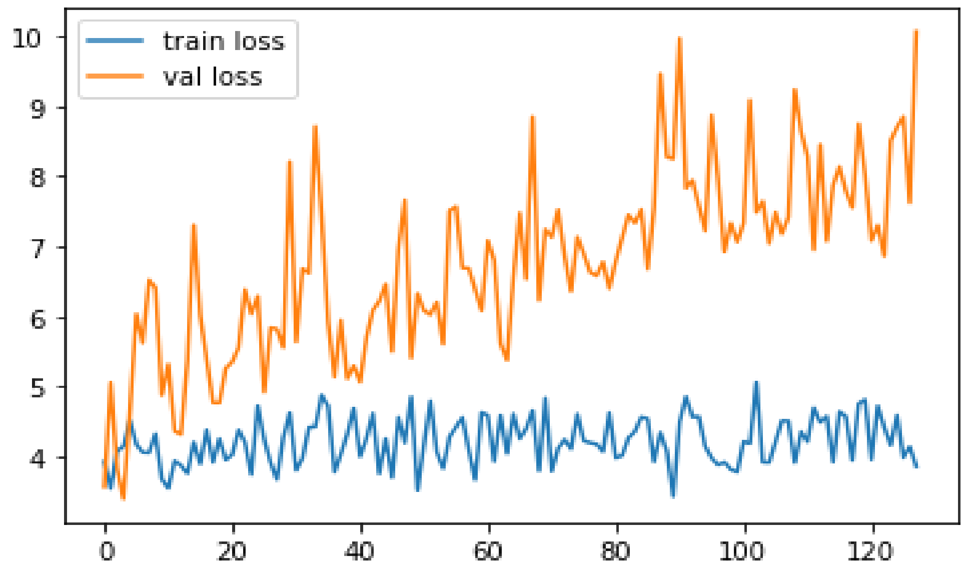

Figure 4.2.1: Train loss and validation loss of EfficientNetB7

Train accuracy and validation accuracy of EfficientNetB7

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

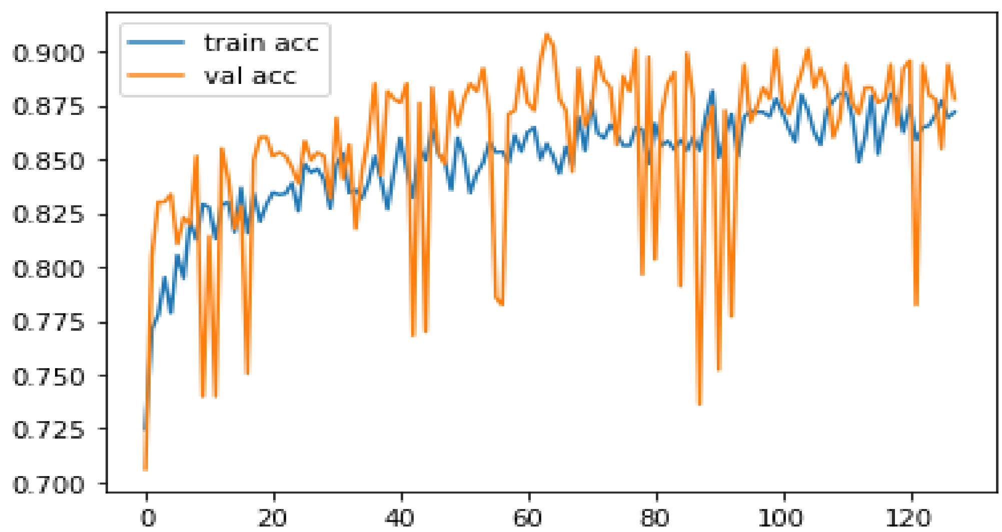

Figure 4.2.2: Train accuracy and validation accuracy of EfficientNetB7

Classification Report of EfficientNetB7

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

TABLE 4.2.3: CLASSIFICATION REPORT OF EFFICIENTNETB7

	Precision	Recall	f1-score
benign	0.85	0.96	0.90
malignant	0.79	0.78	0.83
normal	0.99	0.75	0.85
accuracy			0.85
macro avg	0.91	0.83	0.86
weighted avg	0.89	0.88	0.88

Train loss and validation loss of VGG16

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

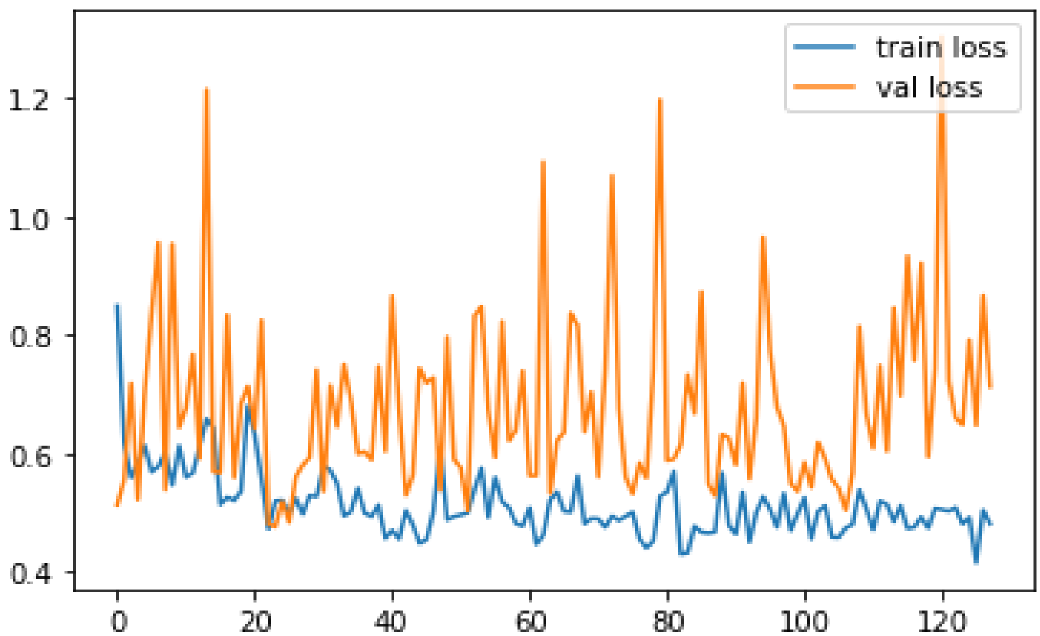

Figure 4.2.4: Train loss and validation loss of VGG16

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%.

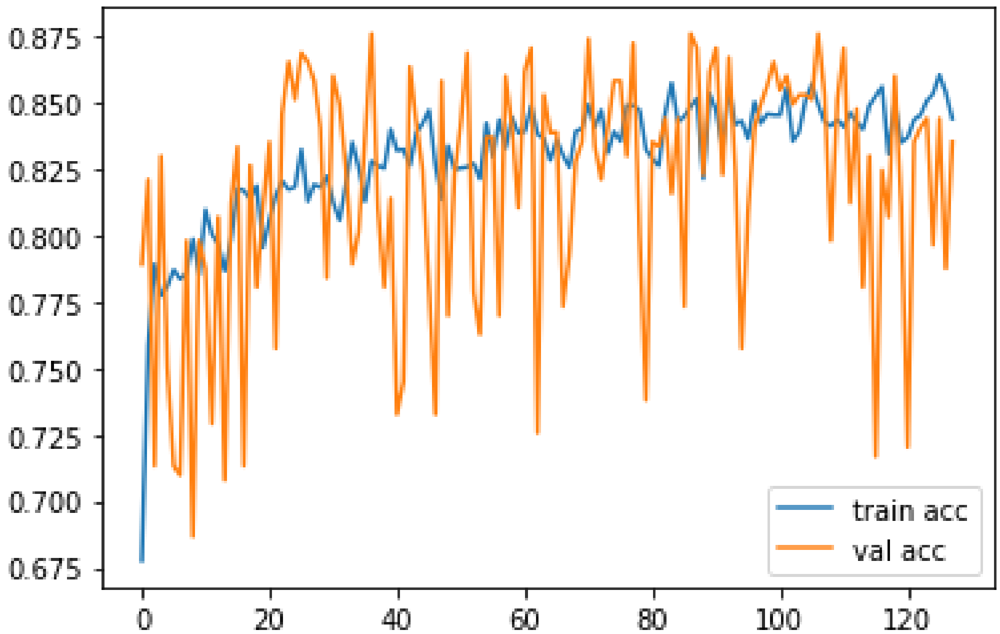

Figure 4.2.5: Train accuracy and validation accuracy of VGG16

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
benign	0.82	0.92	0.87
malignant	0.79	0.78	0.79
normal	0.97	0.67	0.80
accuracy			0.81
macro avg	0.86	0.79	0.82
weighted avg	0.85	0.84	0.83

Train loss and validation loss of Xception

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

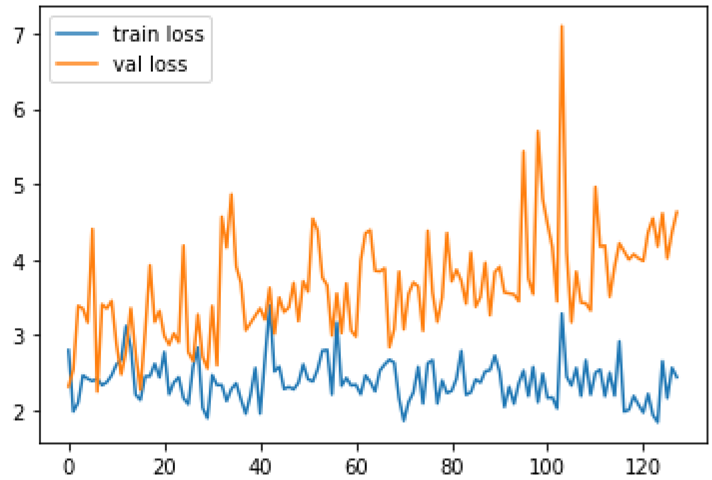

Figure 4.2.7: Train loss and validation loss of Xception

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 85%.

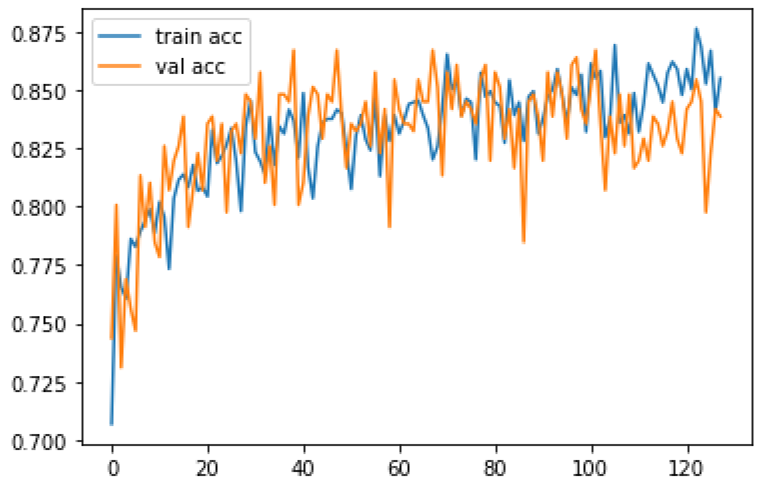

Figure 4.2.8: Train accuracy and validation accuracy of Xception

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
benign	0.83	0.93	0.88
malignant	0.83	0.77	0.80
normal	0.88	0.65	0.74
accuracy			0.85
macro avg	0.85	0.78	0.81
weighted avg	0.84	0.84	0.83

Train loss and validation loss of DenseNet201

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

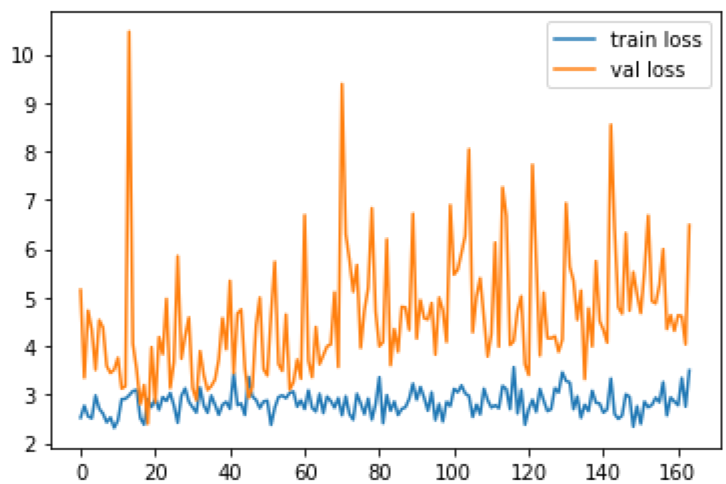

Figure 4.2.10: Train loss and validation loss of DenseNet201

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 88%.

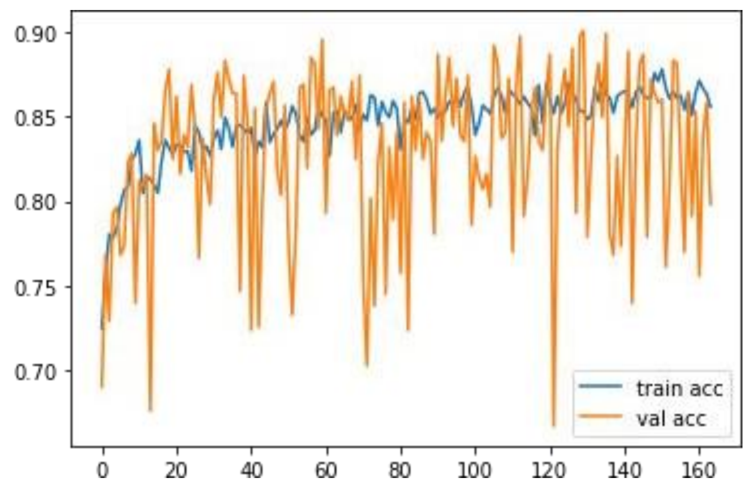

Figure 4.2.11: Train accuracy and validation accuracy of DenseNet201

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
benign	0.96	0.75	0.84
malignant	0.56	0.93	0.70
normal	0.93	0.79	0.86
accuracy			0.88
macro avg	0.81	0.82	0.80
weighted avg	0.86	0.80	0.81

Result Discussion & Analysis

Based on my experimental data, the overall performance of the four CNN architectures appears to be quite similar, with DenseNet201 and EfficientNetB7 achieving slightly higher accuracy than Xception and VGG16. However, it is important to note that the accuracy of a CNN can vary depending on a number of factors, including the specific dataset and task it is applied to, the quality of the training data and the optimization of the model. As such, these results should be considered in the context of the specific application and may not necessarily generalize to other tasks or datasets.

Below is a comparison table summarizing the results:

TABLE 4.3: COMPARISON OF ACCURACY

Model	**Accuracy**
DenseNet201	88%
Xception	85%
VGG16	81%
EfficientNetB7	85%

Overall, it appears that DenseNet201 and EfficientNetB7 achieved the highest accuracy, while VGG16 had the lowest accuracy. Xception had an accuracy that was intermediate between the other three models.

It is worth noting that the accuracy of these models may also be influenced by other factors such as the number of parameters, the complexity of the model, and the amount of computational resources required to train and evaluate the model. For example, EfficientNetB7 has significantly more parameters than the other models and may require more computational resources to train and evaluate, which could impact its performance in certain contexts.

In conclusion, the performance of these four CNN architectures appears to be quite similar, with DenseNet201 and EfficientNetB7 achieving slightly higher accuracy than Xception and VGG16. However, the specific performance of each model may vary depending on the specific task and dataset it is applied to, and other factors such as the number of parameters and computational resources require

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

Impact on Society

I believe my dissertation will help the environment if I explore it in the standpoint of Bangladesh. skin cancer affects a large percentage of Bangladeshi people and many of them are young people. Detecting Skin Cancer at an early stage using Machine 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.

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.

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.

Conclusions

A critical characteristic of my bachelor's degree program is this research. When I commenced my research, I honestly believed even less about machine learning (ML) and 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 machine learning.

Implication for Further Study

The doors have been thrown open. In the disciplines of skin cancer and machine 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 machine 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 Machine 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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