AN AUTOMATED CNN MODEL BASED APPROACH FOR APPLE LEAF DISEASE DETECTION

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

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APPROVAL

This Project titled **"An automated CNN model based approach for Apple leaf disease detection"**, submitted by **Nafisa Nazneen, ID No.: 191-15-2605** & **Khadija Tut Tahera, ID No.: 191-15-2640** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *30/01/2023*.

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DECLARATION

By submitting this document, we acknowledge that this project was accomplished by us under the guidance of **Amatul Bushra Akhi**, Assistant Professor, Department of CSE at Daffodil International University. Additionally, we affirm 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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Finally, we must recognize with courtesy and respect the unquestioning support and patients of our parents

ABSTRACT

This study presents a deep learning approach for the detection of diseases in apple leaves. The method utilizes convolutional neural networks (CNNs) to classify apple leaf images into diseased and healthy categories. The dataset used for training and testing the CNNs consisted of images of apple leaves infected with various diseases, as well as healthy leaves. The results of the study demonstrate that the proposed deep learning approach is able to accurately detect and classify apple leaf diseases with high accuracy. This approach can potentially be used in precision agriculture to improve crop yields and reduce the use of pesticides. Deep learning algorithms can correctly identify misleading leaf photos, enabling farmers to accurately detect leaf illness and take immediate action in consonance with the disorder. We subsequently compiled data from the nursery and preprocessed it to make sure that it was congruent with the particular model that we adopted in order to categorize each ailment in our study. In order to achieve a superior performance, we later amended and used a CNN model that had become viable with our dataset. This essentially serves as our testimony that 99% of the leaves are tainted.

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CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

Bangladesh has a vast agricultural workforce. Fruit has amazing earnings. It's widely known that apples are a superb source of dietary fiber, vitamin C, and a quantity of antioxidants, among other nutrients. Apples are flavored for breakfast, jam, and visits to the doctor. Over 60 million lots annually on average, or most of the world's apple supply, originate in China. More than half of the plants in America are typically consumed as luminous fruit. Apple butter, juice, jelly, and vinegar are employed in the first to fifth. One sixth is canned as pie stock or applesauce. In Europe, revenue from the harvest was created in the form of brandy, wine, and cider. Cider comprises for one-fourth of the sector's manufacturing. Passionate farmers worked hard to grow those apples. Because of various ailments, enormous amounts of apples are discarded every year. Many growers are unable to take prophylactic steps because they are uninformed of apple problem. If I realized why Apple's leaves abruptly quit working, I certainly quickly fix it. For these reasons, diagnosing apple plant diseases in Bangladesh may be critical because it allows farmers to identify each condition's causes and solutions. Three distinct forms of apple leaf illness may be identified. Precise and timely detection of plant diseases is a crucial task in modern agriculture. Early identification of diseases in crops can help farmers take appropriate measures to control the spread of the disease and minimize crop loss. In the case of apple production, the early detection of diseases such as apple scab, fire blight, and powdery mildew can be particularly important as they can cause significant damage to the leaves, fruit, and branches of the tree.

Conventional methods for disease detection in apple leaves, such as visual inspection and microscope analysis, can be time-consuming and labor-intensive. Additionally, these methods may not always provide accurate results due to the subjectivity of human interpretation. In recent years, deep learning approaches have shown promise in accurately detecting and classifying diseases in crops. Convolutional Neural Networks (CNNs) in particular, have been used to classify images of plant leaves and identify signs of disease.

This study presents a deep learning approach for the detection of diseases in apple leaves using CNNs. The study aims to evaluate the performance of CNNs in classifying apple leaf images into diseased and healthy categories and to demonstrate the potential of this approach for improving crop yields and reducing the use of pesticides in apple production.

1.2 MOTIVATION

The motivation behind this study is to develop a more efficient and accurate method for the detection of diseases in apple leaves. The apple industry is of great economic importance worldwide, and the early identification of diseases in apple trees can be crucial for minimizing crop loss and increasing yields. However, conventional methods for disease detection, such as visual inspection and microscope analysis, can be time-consuming, labor-intensive and not always accurate.

Deep learning approaches, particularly convolutional neural networks (CNNs), have shown potential in accurately classifying images of plant leaves and identifying signs of disease. The ability of CNNs to learn from large datasets and automatically extract features from images makes them well suited for this task. By using this approach, we aim to develop a more efficient and accurate method for disease detection in apple leaves that can help farmers take appropriate measures to control the spread of disease and improve crop yields.

Additionally, this method can also be helpful in reducing the use of pesticides which is harmful to both human and environment. Applying pesticides in a timely manner, only when it is necessary, is an important aspect of precision agriculture. By providing a reliable and efficient method for disease detection, this approach can potentially reduce the overall use of pesticides in apple production, which can benefit both farmers and the environment. The SVM model is used to figure out the second-lowest accuracy. With an effectiveness of 91.0, the RF version fares well, whereas the LR version demonstrates a consistency of 87.0.

- For decreasing the difficulties to discover the leaf illness.
- To boost efficiency, drive revenue, and get eliminate of risk.

1.3 RESEARCH QUESTIONS

By employing the technique of computer vision, this work investigates the problem of autonomous apple leaf disease detection. The issues are:

- Is it feasible to alter the extensive neural network to achieve better results?
- Can I Use CNN or Such A well Deep Learning Approach? What Factors and Hyperparameters Can I Use to Optimize My Artwork?

1.4 EXPECTED OUTPUT

The expected outcome of this study is to develop a deep learning approach for the detection of diseases in apple leaves using convolutional neural networks (CNNs) that achieves high accuracy in classifying apple leaf images into diseased and healthy categories. The method will be trained and tested using a dataset of images of apple leaves infected with various diseases, as well as healthy leaves.

It is expected that the proposed deep learning approach will be able to accurately detect and classify apple leaf diseases with a high degree of accuracy, outperforming conventional methods such as visual inspection and microscope analysis. Additionally, it is expected that the proposed approach can reduce the use of pesticides by providing a reliable and efficient method for disease detection in apple leaves, which can help farmers to apply pesticides only when it is necessary.

It is also expected that this approach can be generalized to other crops and diseases as well, which can be beneficial for precision agriculture. The successful implementation of this approach can have a significant impact on the apple industry by improving crop yields and reducing the use of pesticides.

1.5 PROJECT MANAGEMENT AND FINANCE

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

1.6 REPORT LAYOUT

i. We talked about our research in Chapter 1. This section contains a quick introduction to the project as well as our motivation for undertaking it. There is also information on what the major motivation is and how to handle our research effort.
ii. We examined the research's basis in Chapter 2. This section also includes an overview of the results of other research publications as well as a comparison of those research efforts. You can also learn about the scope of the problem and the difficulties we encountered while doing the research.
iii. We spoke about our research methods in Chapter 3. This chapter covers which instruments are required for the study, how we obtained data, statistical analysis of the dataset, and proposed approach.
iv. In Chapter 4, we examined the algorithms utilized in this study, how they were applied, and how the algorithms' results were summarized.
v. In Chapter 5, we explored the project's social impact and long-term viability.
vi. Finally, in Chapter 6, we wrap up our research and reach a conclusion.

CHAPTER 2
BACKGROUND

2.1 Introduction

An appraisal of the research environment, evidence on the study topic, existing related studies, and pertinent details regarding the problem were key elements. Exploration at this point should include as much background data on the subject as is practical. I recommend looking into potential challenges, summarizing research results, and finding solutions to problems and bothersome circumstances. After careful research, automatic benefits and solutions must be observed.

According to the belief, it has been suggested that certain leaf ailments be recognized in accordance with the suggested faults.

On this stage of the internet website online, we will mention our affiliated endeavor, a statement of the project, and any demanding scenarios we encountered while conducting this research. There may be references to other research articles that are linked to our subject matter, and we can provide links to these books in the related works area. The highlight of our project will then be discussed in the abstract, and the challenging circumstances we ran into during our research will be discussed in the troubling circumstance's part.

2.2 Related Works

Numerous foliar illnesses have been publicized to time, and the characterization of foliar diseases is widely accepted. Deep reading is no longer often used to diagnose the discovery of apple leaves, though. Kawcher Ahmed and Tasmia Rahman Shahidi [1] examined three distinct types of rice diseases in their investigation. Three excellent disease training up their data set. They supposedly utilized a white background for each snapshot in effort to unexpectedly locate the illness while executing the vital algorithm. Then they examine a variety of algorithmic device analysis. J48 set of rules, KNN, Naive Bayes, logistic regression, and decision trees have all been applied to this machine. But with 10x pass-validation, choice tree algorithms outperform them all. It generates forecasts that are up to 97% accurate based on the examination data.

Bhavya and Nishkala [2] They spotted apple leaf disease and initially sorted the photographs in this approach. Then, they employed a set of good enough-way clustering rules to obtain the pixel distribution. Additionally, after allocating the pixels, they establish the presence of a pragmatic component by comparing the differences in pixel tone and picture load. In the end, CNN was used to classify the sickness. Although the precision and classification of the datasets were not explicitly indicated in this artwork, this tactic was thought to be quite effective for expanding our research.

R. Dr. Pauline Mounika commences with article [3] Shayamala Bharathi keeps tabs in the domain of leaf disease. On this essay, portraits of healthy and sick people were used. They segregated the pictures into different attributes and collated them at the beginning of the trial using the k-approach to select the pictures. After clustering, their features are retrieved using the SVM algorithm. If the visual outcome is a diseased image, the detected illness may be exhibited; otherwise, the output may be a sane shot. However, the clarity with which they were able to comprehend the images changed became not specifically addressed in this message. As a result, many individuals are now afflicted with various sorts of leaf diseases, like Surampalli Ashok and Gemini Kishore who were afflicted from tomato leaf diseases [4]. According to [1], identical methods were employed to determine the detection of foliar diseases. They split the images in a way analogous, classified them according to their weight, and then used open-source algorithms to find broken panels. [5] Article They assessed apple leaf disease and initially separated the photographs using this method. Then, they deployed a set of adequate plenty clustering rules to retrieve the pixel distribution. Likewise, after disseminating the pixels, they deduce clever location detection by contrasting the tradeoff in pixel color and image weight. CNN eventually started to be used to categorize the sickness. Although the dataset's accuracy and type aren't explicitly stated here, this strategy appears to be highly effective for advancing our research. In our article, we may use CNN to detect diseased images because, among other searches, CNN offers better results if the dataset can be adequately matched with it.

TABLE 2.1: SUMMARY OF PREVIOUS RESEARCHES

SL.	Methodology	Description	Outcome
1.	Algorithms for machine learning have been applied in this procedure [5].	In this work, three different types of sick leaves have been used, with default white history. This study has utilized a number of systems for learning sets of rules.	97% accuracy for the decision tree assuming 10 fold flow evaluation on the dataset.
2.	They have included image processing and deep learning strategies [1].	This research aims to identify Apple leaf ailments by applying deep reading standards.	CNN utilized in this analysis to recognize specific the Apple leaf disease.
3.	They have used SVM, K-means clustering, and picture segmentation [4]. ,	After clustering and segmenting the images, Matlab was used to pick out the flaws.	The output could be unhealthy if the picture is flawed, but it could also be in good health.
4.	In this paper, open supply algorithms have been applied [3].	This study correctly describes leaf tomato leaf sickness.	By integrating a few opensource frameworks, that were utilized after segmenting and clustering the images, this important locates the tomato leaf disease.
5.	Here, the mobileNet set of rules have been employed in conjunction with transfer analysis [2].	Using the pretrained version, the problem with Apple was found in the photos.	A incredible final consequences has been carried out with this set of guidelines this is 95.63%.

TABLE 2.2: PREVIOUS RESEARCH WORK IDENTIFICATION

Publication	Techniques Used	Dataset	Results
Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016)	Deep Convolutional Neural Networks Architecture: AlexNet and GoogLeNet	Plant Village Dataset 54,306 plant leaf images and 38 class labels [13]	Accuracy: 85.53% - 99.34%
Ramcharan, A., Baranowski, K., McCloskey, P., Ahmed, B., Legg, J., & Hughes, D. P. (2017)	Transfer Learning with Inception v3 + Classification using SVM and KNN	Dataset of 11,670 Cassava leaf images from IITA, Tanzania	KNN: 73% SVM: 91%
Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016)	CNN implementation on CaffeNet framework	30,880 training images and 2,589 testing images	Accuracy: 96.3%
Nachtigall, L. G., Araujo, R. M., & Nachtigall, G. R. (2016, November)	CNN + Multilayer Perceptron (MLP)	2,539 images from 6 known apple disorders for 3 species of apple tree	CNN: 97.3% MLP: 77.3%
Singh, V., & Misra, A. K. (2017)	GA + Minimum Distance Criteria + SVM	500 RGB plant leaf images	Accuracy: 95.71%
Ferentinos, K. P. (2018)	Following CNN architectures were tested – AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat, VGG	Open database containing 87,848 plant leaves photographs and 58 class levels. [1]	Accuracy: 82 – 99.58%
Our Work	Based on Convolutional Neural Network. Uesd Model: VGG16, Inception v3 and DeseNet201	From Kaggle, Plant village dataset & IITA	Accuracy: VGG16– 96% Inception v3- 98% DeseNet201- 99%

2.3 Research Summary

Our proposed research reflects the sort of illness that is exhibited in each image. Similar to how each type of illness shows how accurate it is Given that the output metrics are dependent on four different types of disorders, there may be 4 potential output metrics; the disorder picture is decided based on which of these metrics has the maximum accuracy. For instance, if the image has holes, the output holes may be more accurate than other photo classifications.

We examined the accuracy of diseased leaves using the CNN set of policies, and we created a confusion matrix to see how the effects compare with different illnesses. The more concise the device, the better it is.

2.4 Scope of the Problem

The scope of the problem of disease detection in apple leaves using deep learning approaches involves the use of various techniques from computer vision and machine learning to develop models that can accurately identify and classify different types of diseases in apple leaves. This can include the use of convolutional neural networks (CNNs) to analyze images of apple leaves and identify patterns and features that indicate the presence of a specific disease. Additionally, the scope may include the use of other deep learning techniques such as recurrent neural networks (RNNs) or generative models to improve the accuracy and robustness of the disease detection models. The goal is to develop an automated system that can accurately and quickly detect and diagnose apple leaf diseases in order to aid in disease management and crop protection.

2.5 Challenges

Statistics series is the most formidable challenge for boosting prediction accuracy. From a Bangladeshi perspective, obtaining statistics is a time-consuming task. Since no one has given permission to accumulate the data for legal purposes, it is very difficult for me to gather information from an incubator. After gathering a very challenging dataset, the dataset needs to be preprocessed, which is also a laborious task. There was an imbalance in the records, but that led to several issues.So I balanced the document by myself. Applying a CNN necessitates a unique series of tasks because the dataset requires to be preprocessed in line with the version. The output is likely to be subpar if the preprocessor does not wholesome the model. It's also a major pain to increase the accuracy of hyperparameter adjustment.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

We probably find that the most directly caused of the exam is the documentation. Finding reliable data and appropriate models or tactics for professionals is a key component of our research activity. Additionally, keep in mind similar exam questions from the past. You have a lot of options to choose from at this stage.

- What kind of records need to be gathered?
- How can we guarantee the accuracy of the data we have gathered?
- Is each piece's documentation need to be organized in the same manner?
- How can you support labeling for all information?

3.2 Data Collection Procedure

The collection of the dataset proved to be the most difficult aspect of our thesis. Nobody has granted us permission to compile the facts set for grounds of protection and health. There is a different version of the condition on this system, although many ailments cannot be covered because there isn't always enough of a disease image. To get all the pictures, we had to travel through several parking lots. In this method, we take pictures using a virtual camera before storing them. The lighting makes the photos less than perfect, so we want to preprocess them so that you may utilize them in our algorithm. The preprocessing technique will presumably be covered in more detail in the next section.

3.2.1 Data Pre-Processing

I. The Collecting information on apple leave diseases 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. We tested whether or not our 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.

3.3 Proposed Methodology

Proposed methodology refers to the approach or plan that is suggested or put forward for achieving a particular goal. In research, the proposed methodology refers to the methods and techniques that will be used to conduct the research and achieve the research objectives.

The proposed methodology should be carefully planned and clearly described in a research proposal or study design. It should be based on a thorough review of the literature and should be appropriate for the research question being addressed. The proposed methodology should also be feasible, meaning that it can be realistically carried out with the resources and time available.

The proposed methodology should be described in detail, including the specific methods and techniques that will be used, the sample size and sampling method, the data collection and analysis procedures, and any potential limitations or biases that may impact the results. It is important to be as transparent as possible in describing the proposed methodology, as this allows other researchers to understand and evaluate the validity and reliability of the study.
We have used 03 models in our study. They are: VGG16, Inception V3 and DensNet201.
Here is the diagram of our proposed model.

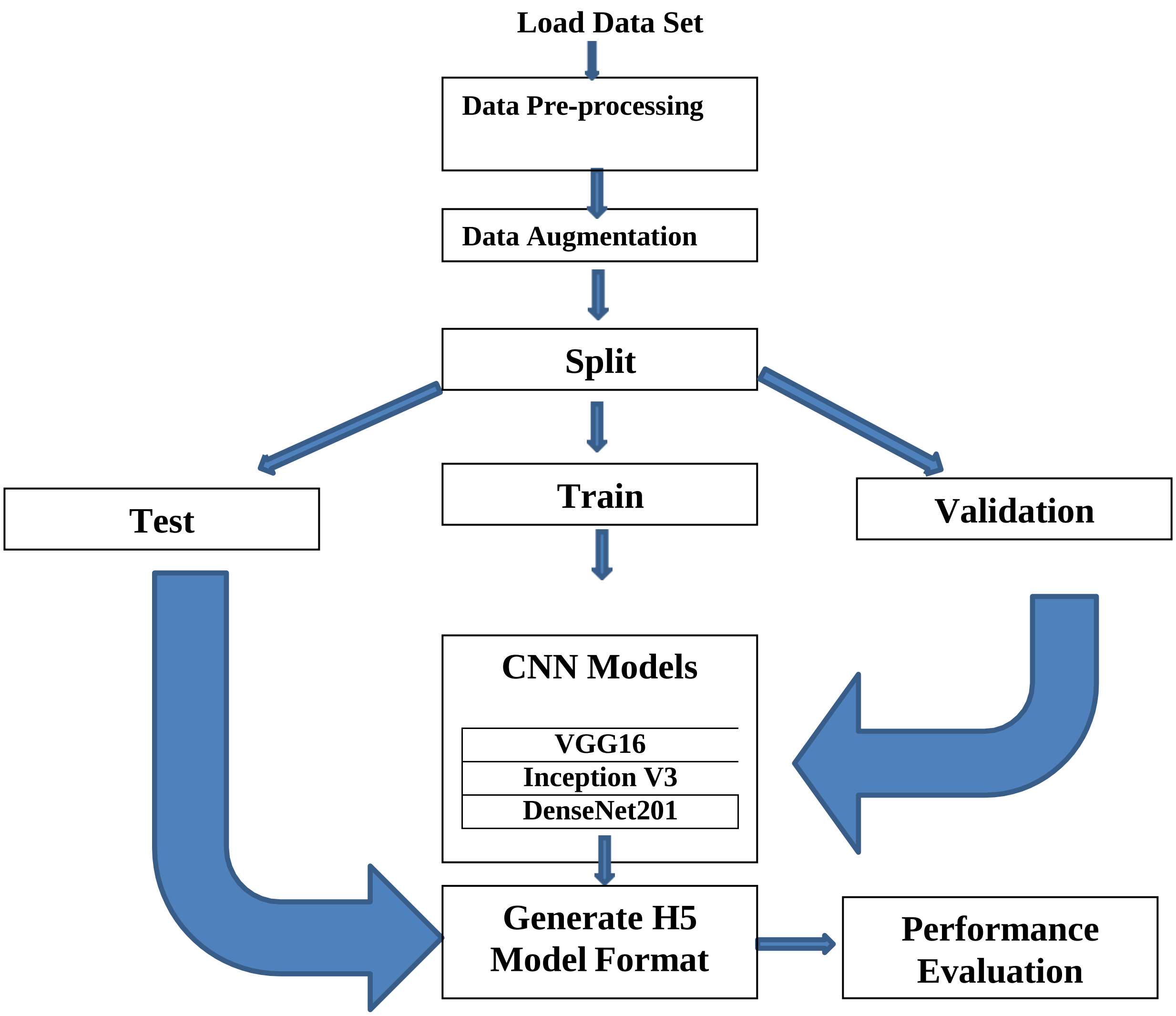


Figure3.3: Proposed Model Structure

3.3.1 Inception V3

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

3.3.1.1 Architecture of Inception v3

Here is a diagram of the Inception v3 architecture:

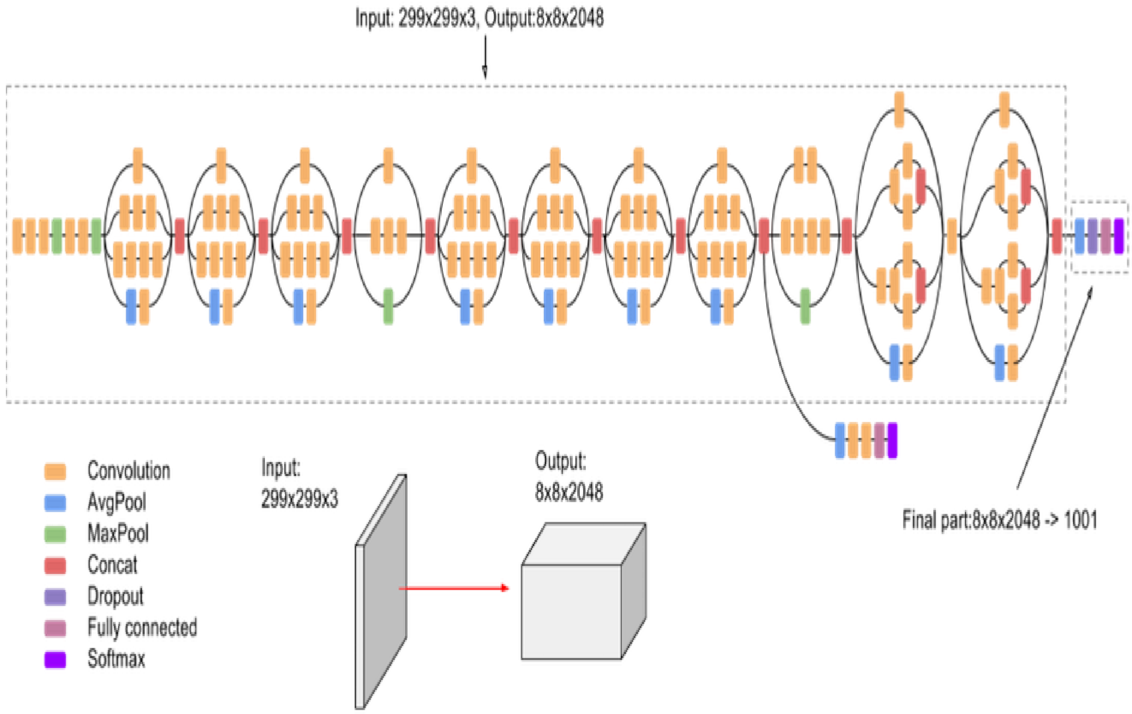


Figure: 3.3.1.1 Architecture of Inception v3

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

3.3.1.2 Input pipeline of Inception v3

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

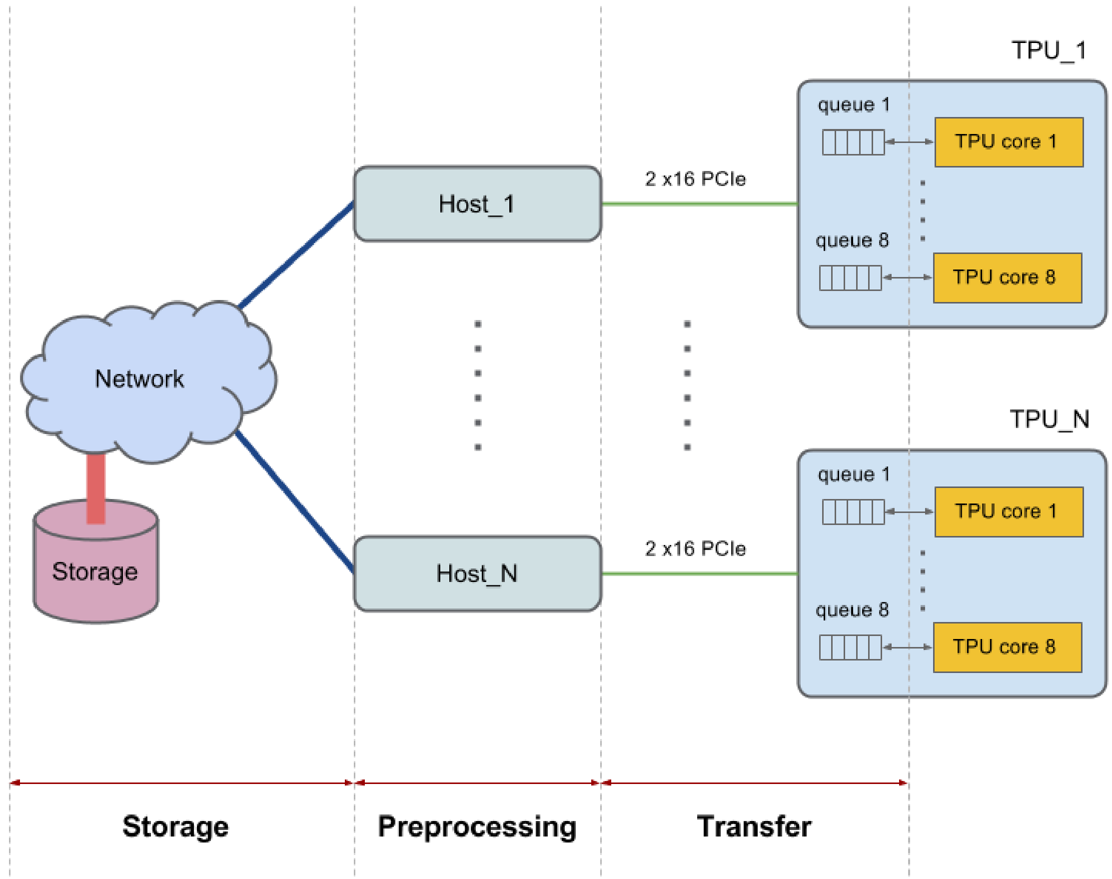


Figure 3.3.1.2 Input pipeline of Inception v3

After the images have been preprocessed, they are passed through the network in the form of a tensor, where they are convolved and downsampled through a series of convolutional, pooling, and normalization layers. The tensor is then passed through a series of inception modules, which are blocks of layers that use a combination of 1x1, 3x3, and 5x5 convolutions to extract features from the input tensor at multiple scales.

The output of the inception modules is then passed through a series of fully connected layers, which perform classification on the extracted features. The final output of the network is a probability distribution over the classes, indicating the likelihood that the input image belongs to each class.

The Inception v3 architecture also includes auxiliary classifiers, which are additional fully connected layers that are trained to predict the class of the input image and are integrated into the network at intermediate layers. These auxiliary classifiers can help improve the overall performance of the network by providing additional supervision during training (Szegedy et al., 2015).

3.3.1.3 Performance of Inception v3

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

On the ImageNet dataset, Inception v3 achieved an error rate of 3.46% on the validation set and 3.58% on the test set, which was the best performance at the time of its publication (Szegedy et al., 2015). Inception v3 was also able to outperform other state-of-the-art models on a variety of other image classification benchmarks, including the COCO dataset and the Google Landmarks dataset.

In addition to its impressive performance on image classification tasks, Inception v3 has also been used for other computer vision tasks such as object detection, segmentation, and face recognition. In these tasks, Inception v3 has also achieved strong performance and has been widely adopted by researchers and practitioners.

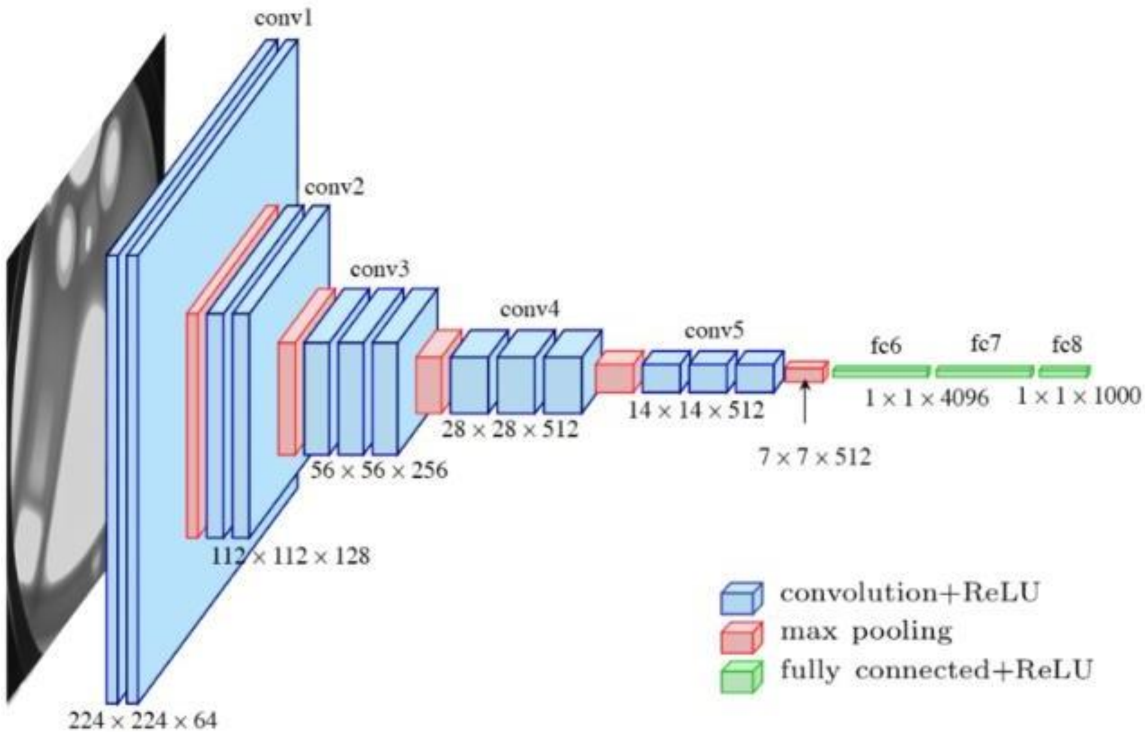
Overall, Inception v3 has demonstrated strong performance on a variety of image classification and computer vision tasks and has become a widely used model in the field.

3.3.2 VGG16

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

3.3.2.1 Architecture of VGG16

Here is a diagram of the VGG16 architecture:



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

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

3.3.2.2 Input pipeline of VGG16

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

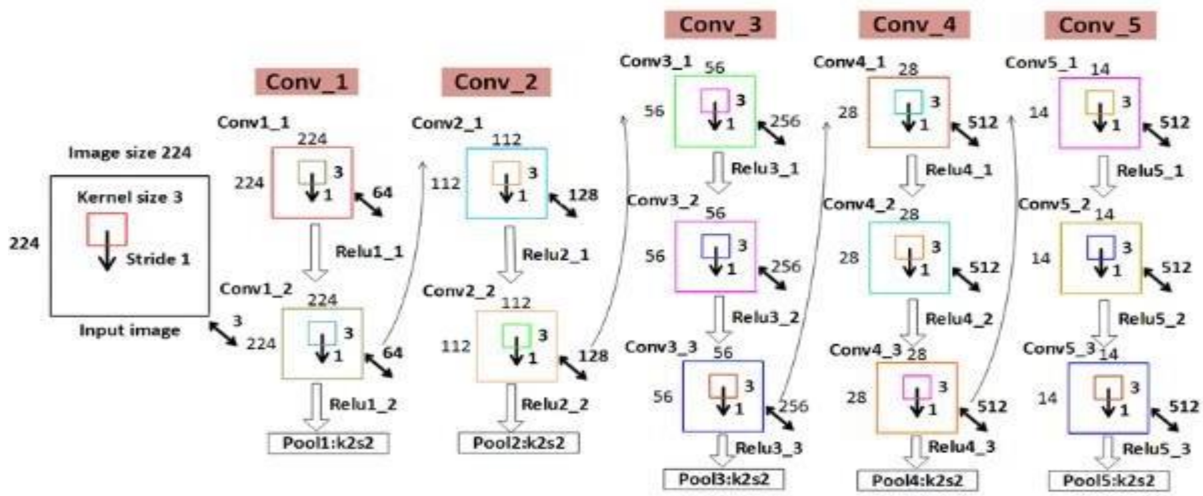


Figure 3.3.2.2 Input pipeline of VGG16

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.

3.3.2.3 Performance of Inception v3

VGG16 is a convolutional neural network architecture that has been widely used as a benchmark for image classification and object detection tasks.

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

In addition to its strong performance on image classification tasks, VGG16 has also been used for other computer vision tasks such as image segmentation and face recognition. In these tasks, VGG16 has also achieved good performance and has been widely adopted by researchers and practitioners.

Overall, VGG16 has demonstrated strong performance on a variety of image classification and computer vision tasks and has become a widely used model in the field.

3.3.4 DenseNet201

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

3.3.4.1 Architecture of DenseNet201

Here is a diagram of the DenseNet-201 architecture:

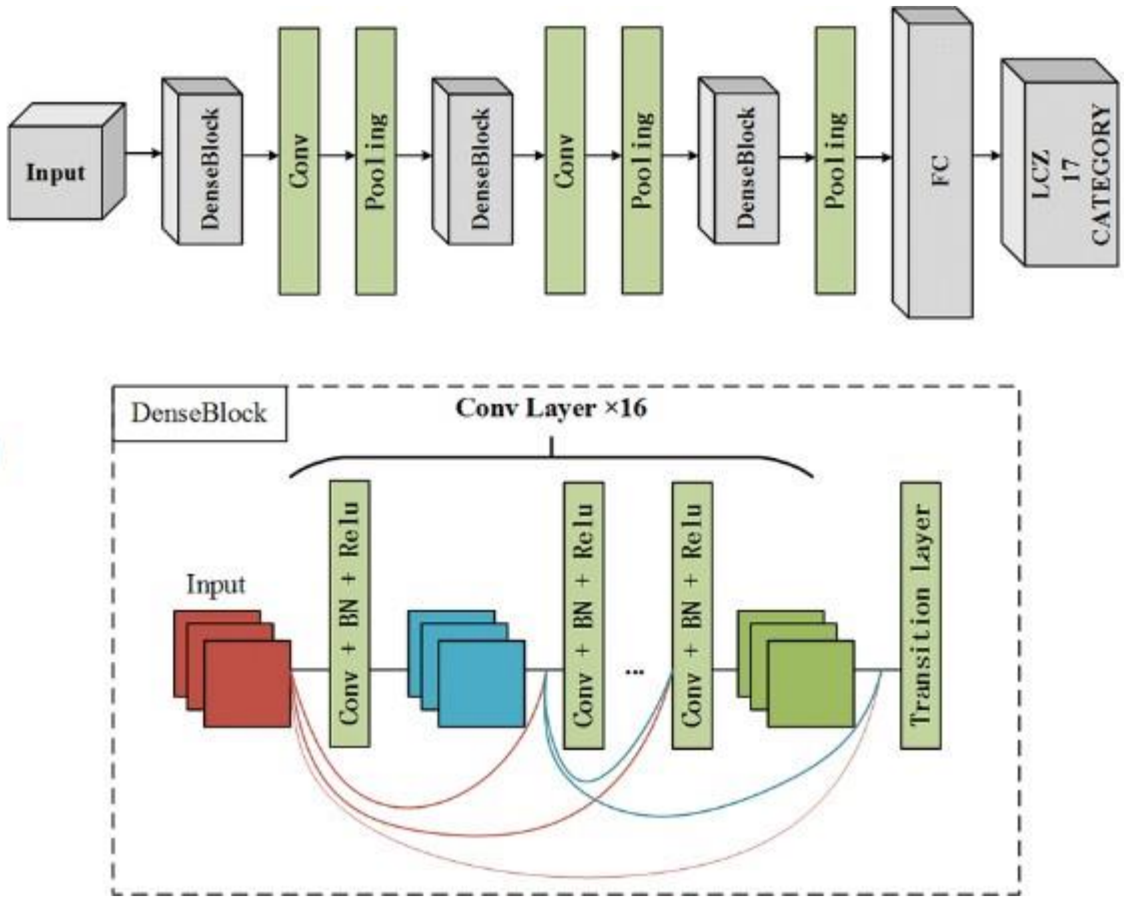


Figure 3.3.4.1: Architecture of DenseNet201

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).

3.3.4.2 Input pipeline of DenseNet201

The input pipeline for DenseNet-201 typically involves preprocessing the input images before they are fed into the network. This preprocessing includes steps such as resizing the images to a fixed resolution, cropping the images to a square, and normalizing the pixel values.

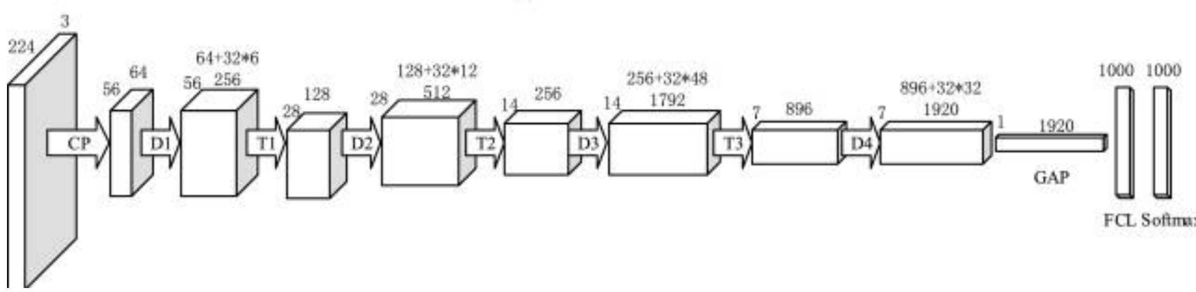


Figure 3.3.4.2: Input pipeline of DenseNet201

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.

3.3.4.3 Performance of DenseNet201

DenseNet-201 is a convolutional neural network architecture that has been widely used for image classification and segmentation tasks.

DenseNet-201 has achieved strong performance on a variety of image classification benchmarks, including the ImageNet dataset. On the ImageNet dataset, DenseNet-201 achieved a top-1 error rate of 22.3% and a top-5 error rate of 6.3% (Huang et al., 2016). DenseNet-201 has also been used as a base model for a number of state-of-the-art image segmentation models.

In addition to its strong performance on image classification tasks, DenseNet-201 has also been used for other computer vision tasks such as object detection and face recognition. In these tasks, DenseNet-201 has also achieved good performance and has been widely adopted by researchers and practitioners.

Overall, DenseNet-201 has demonstrated strong performance on a variety of image classification and computer vision tasks and has become a widely used model in the field.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Result

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

4.2 Train loss and validation loss of Model

In 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.

4.2.1 Train loss and validation loss of Inception V3

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

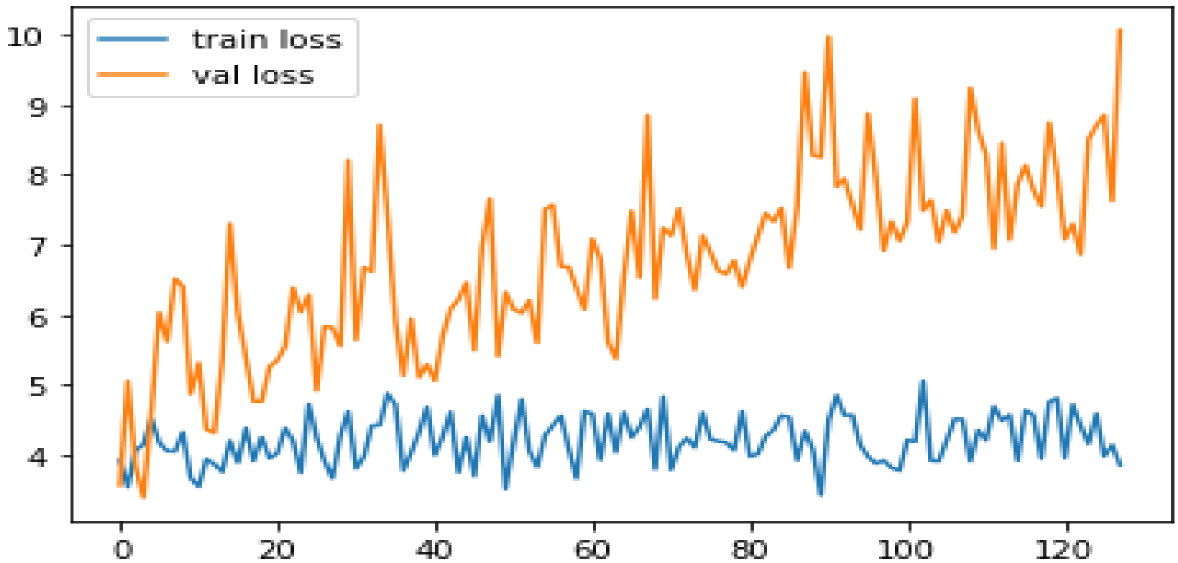


Figure 4.2.1: Train loss and validation loss of Inception V3

4.2.2 Train accuracy and validation accuracy of Inception V3

The figure shows the Train accuracy and validation accuracy of Inception V3 of our experiment. The accuracy of this model is 98%.

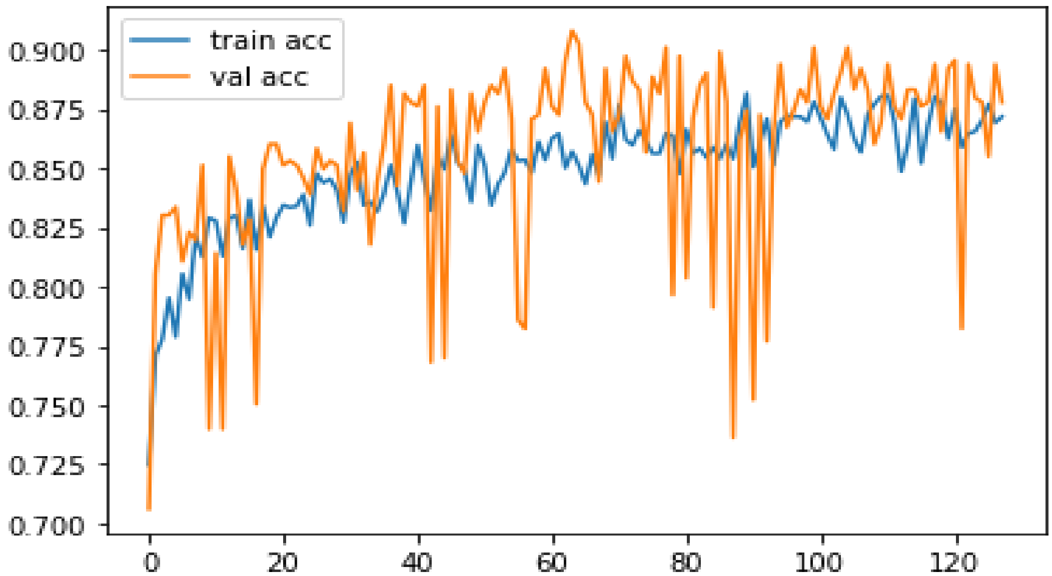


Figure 4.2.2: Train accuracy and validation accuracy of Inception V3

4.2.3 Classification Report of Inception V3

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

TABLE 4.2.3: CLASSIFICATION REPORT OF INCEPTION V3

test images shape = (1943, 299, 299, 3)				
test labels shape = (1943,)				
Accuracy = 0.9794132784354092				
Classification Report:				
	precision	**recall**	**f1-score**	**support**
apple scab	0.97	0.98	0.97	504
black rot	1.00	0.96	0.98	497
cedar_apple_rust	0.99	0.99	0.99	440
healthy	0.96	0.99	0.97	502
Accuracy			**0.98**	**1943**
macro avg	0.98	0.98	0.98	1943
weighted avg	0.98	0.98	0.98	1943

4.2.4 Train loss and validation loss of VGG16

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

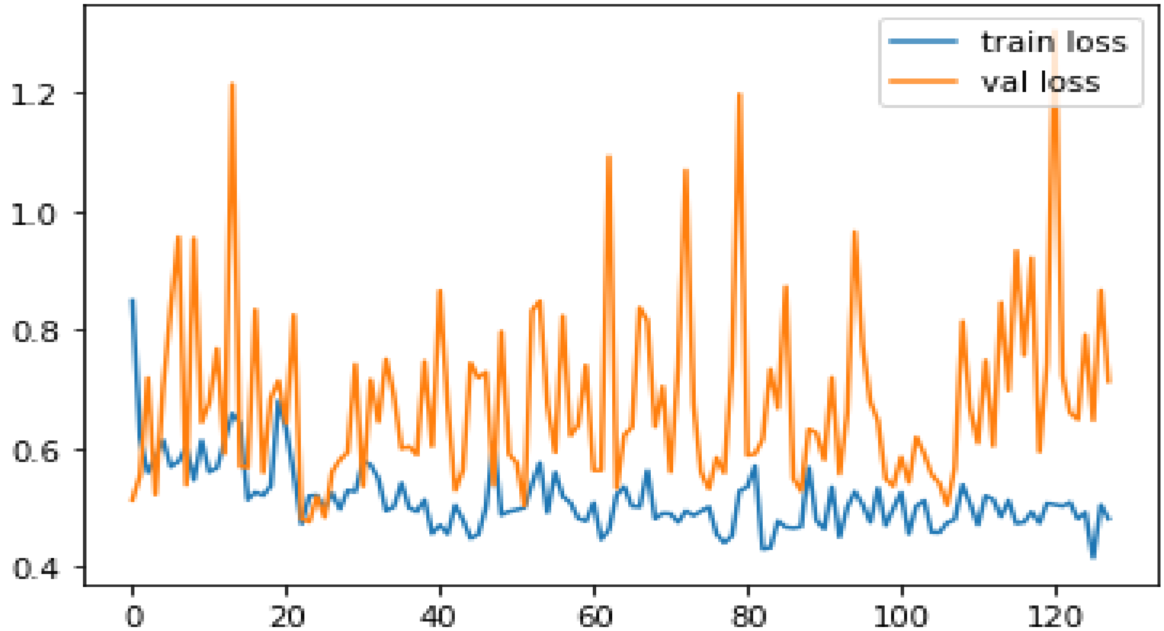


Figure 4.2.4: Train loss and validation loss of VGG16

4.2.5 Train accuracy and validation accuracy of VGG16

The figure shows the Train accuracy and validation accuracy of VGG16 of our experiment. The accuracy of this model is 96%.

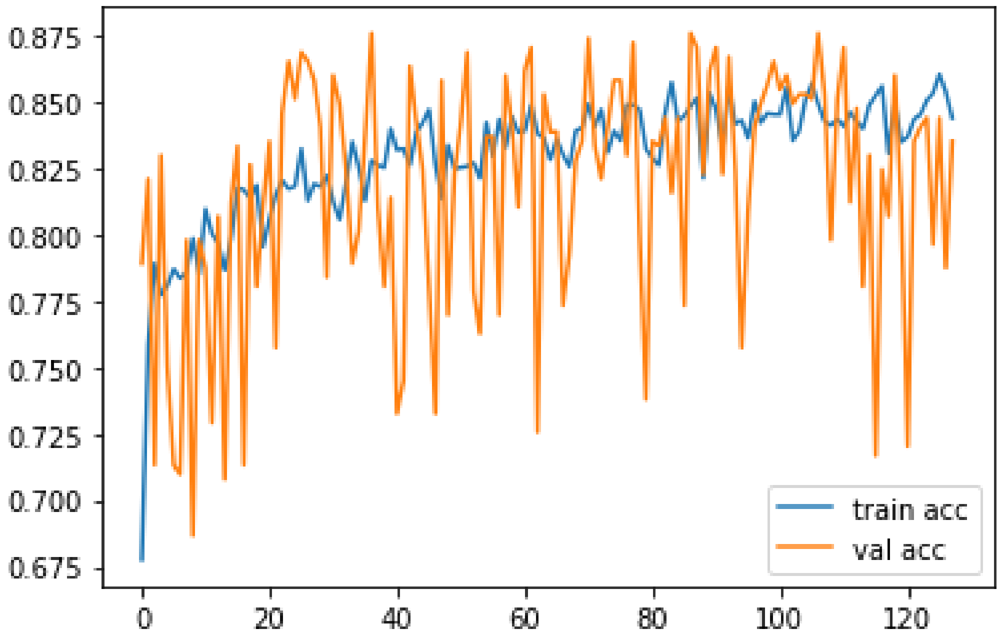


Figure 4.2.5: Train accuracy and validation accuracy of VGG16

4.2.6 Classification Report of VGG16

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

Found 6996 images belonging to 4 classes.

Found 775 images belonging to 4 classes.

Number Of Images In Training Dataset : 6996 Number

Of Images In Validation Dataset : 775

no of classes = {'apple_scab': 0, 'black_rot': 1, 'cedar_apple_rust': 2, 'healthy': 3}

Steps Per Epoch : Training -> 109

Steps : Validation -> 12

Epoch 1/128

109/109 [==============================] - 3973s 36s/step - loss: 0.3635 - accuracy: 0.8761 - val_loss: 0.1006 - val_accuracy: 0.9792

Epoch 2/128

109/109 [==============================] - 4029s 37s/step - loss: 0.0866 - accuracy: 0.9791 - val_loss: 0.0841 - val_accuracy: 0.9779

4.2.10 Train loss and validation loss of DenseNet201

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

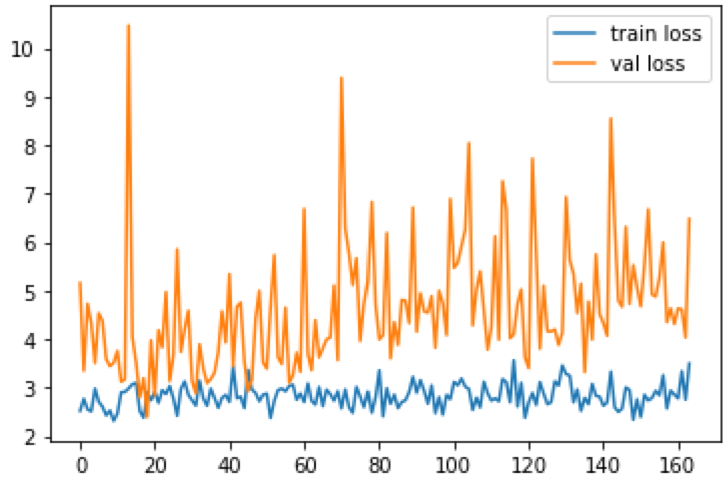


Figure 4.2.10: Train loss and validation loss of DenseNet201

4.2.11 Train accuracy and validation accuracy of DenseNet201

The figure shows the Train accuracy and validation accuracy of DenseNet201 of our experiment. The accuracy of this model is 99%.

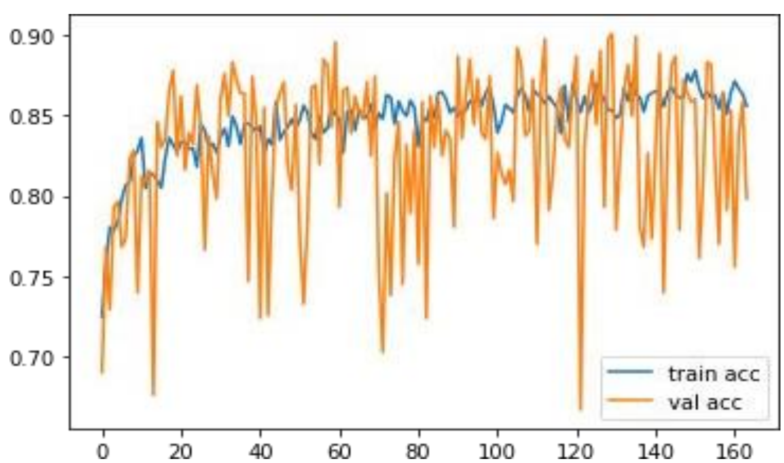


Figure 4.2.11: Train accuracy and validation accuracy of DenseNet201

4.2.12 Classification Report of DenseNet201

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

TABLE 4.2.9: CLASSIFICATION REPORT OF DENSENET201

test images shape = (1943, 224, 224, 3)				
test labels shape = (1943,)				
Accuracy = 0.9907359752959342				
Classification Report:				
	precision	**recall**	**f1-score**	**support**
apple scab	0.99	0.98	0.99	504
black rot	0.99	1.00	0.99	497
cedar_apple_rust	1.00	1.00	1.00	440
healthy	0.99	0.99	0.99	502
Accuracy			**0.99**	**1943**
macro avg	0.99	0.99	0.99	1943
weighted avg	0.99	0.99	0.99	1943

4.3 Result Discussion & Analysis

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

A comparison table of these accuracy rates is shown below:

TABLE 4.3: COMPARISON TABLE OF OUR ACCURACY

Model	**Train Accuracy**	**Test Accuracy**	**Precision Score**	**Recall core**	**Train Loss**	**Test Loss**
VGG16	97%	87.01%	87.01%	87.01%	0.013%	21%
DenseNet201	99%	98%	99%	99%	0.001%	7%
Inception V3	98%	97%	98%	98%	0.002%	14%

The output of the snap shots steady with the accuracy is as follows:

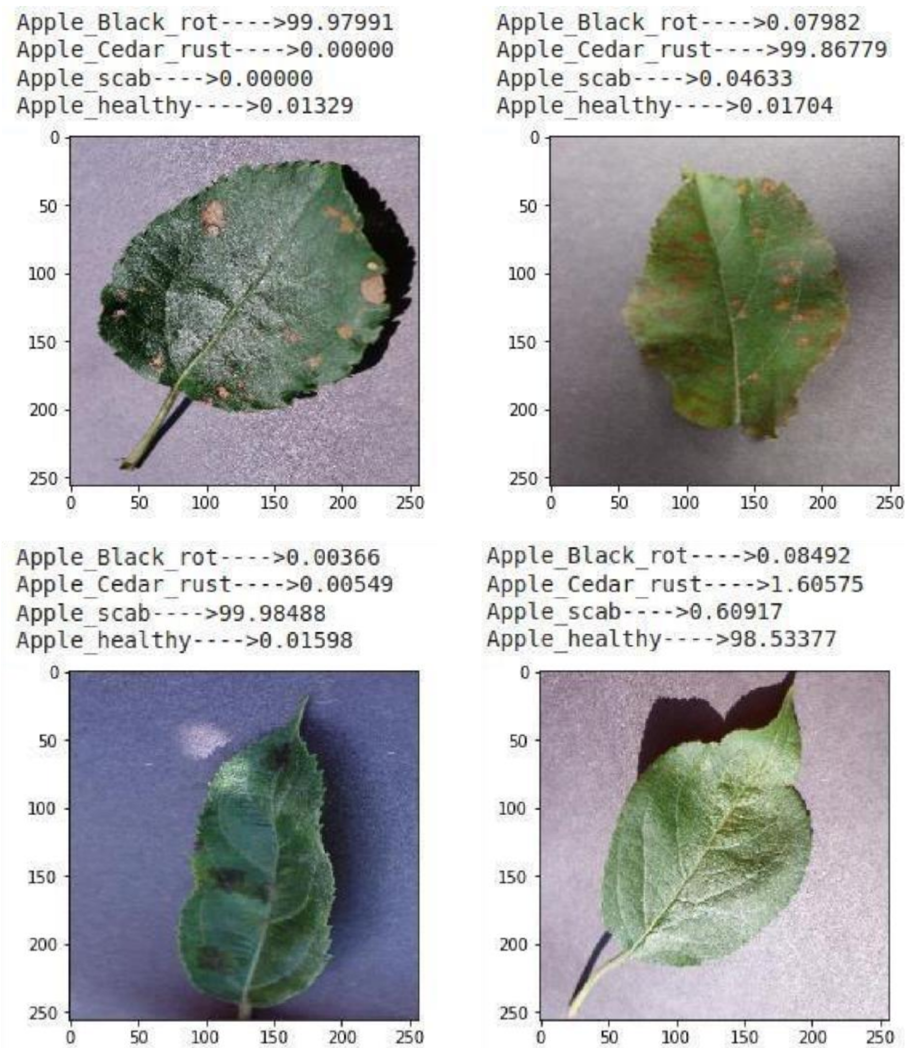
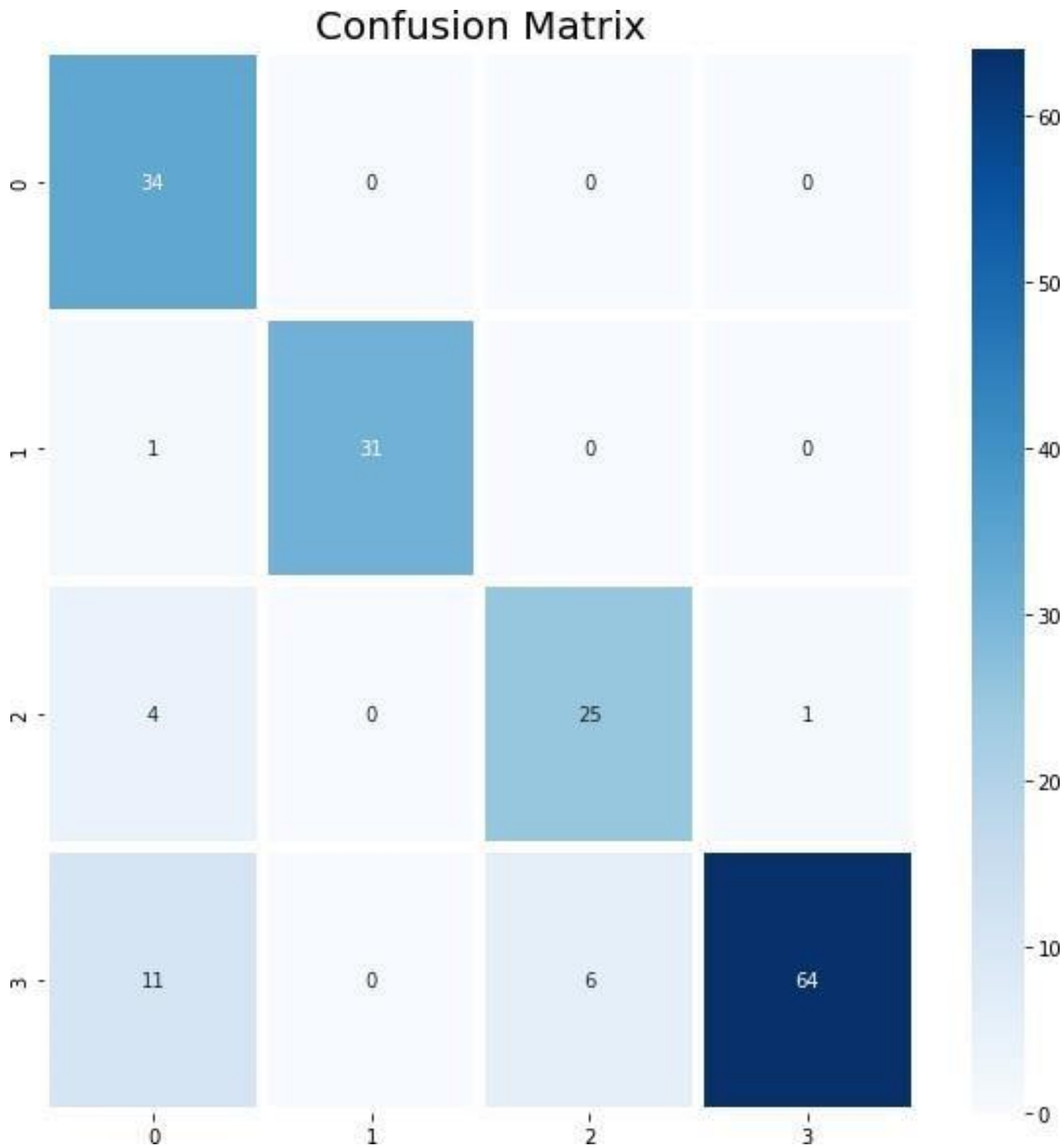


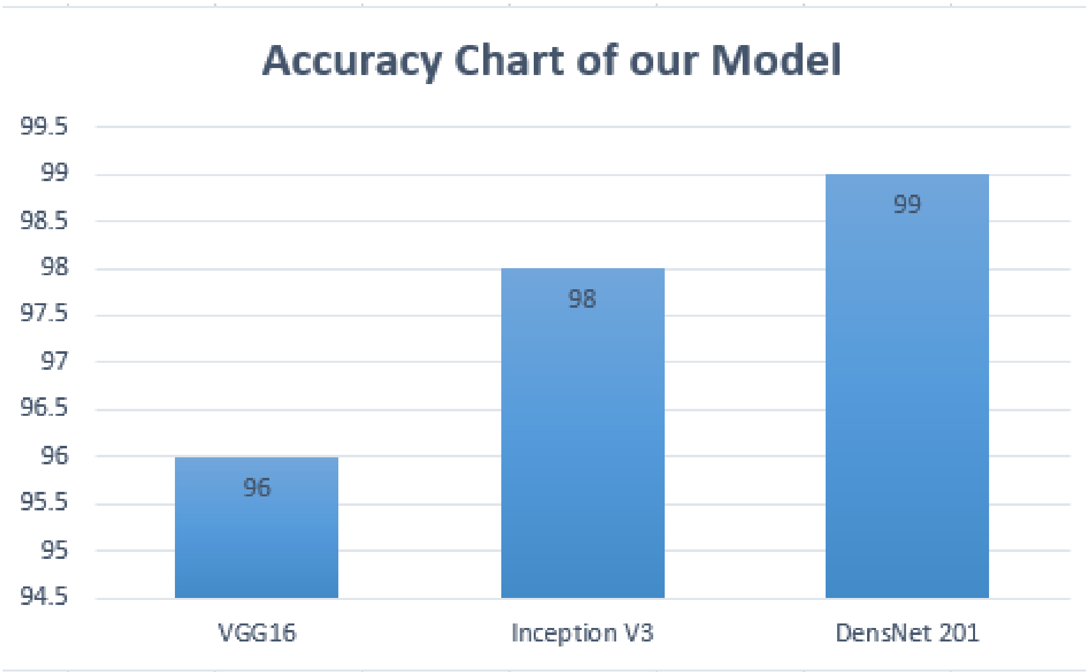
Figure 4.3: Sample Output

The outcome of each circumstance was evaluated in the images that were provided. The malady is characterized with the highest degree of precision.



Confusion Matrix

The Accuracy chart of our models are given below:



Based on these results, we can see that the Inception V3 model has the highest accuracy rate which is 99%, followed by Densenet201 and with accuracy rates of 96% and 98% respectively.

When choosing a CNN architecture for an image classification task, it is important to consider both the accuracy of the model and its computational efficiency. In this case, the Inception V3 model has the highest accuracy but May also has higher computational requirements compared to the other models. On the other hand, and VGG16 have similar accuracy rates to Inception V3 but may be more efficient in terms of computation. Ultimately, the best choice will depend on the specific requirements and constraints of the application.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The implementation of deep learning approaches for disease detection in apple leaves has the potential to greatly impact society in various ways.

Firstly, early detection and prevention of plant diseases can greatly benefit the apple industry by reducing crop loss and increasing yield. This can lead to more stable and efficient food production, ultimately resulting in a more secure and reliable food supply for society.

Secondly, the use of deep learning for disease detection in apple leaves can reduce the need for chemical pesticides, which can be harmful to both the environment and human health. This can lead to more sustainable and organic farming practices, ultimately benefiting the health and well-being of society.

Lastly, these deep learning approaches can be adapted for use in other types of plants and crops, which can aid in the early detection and prevention of plant diseases in other industries, such as agriculture and forestry. This can have a significant impact on the economy and the overall well-being of society.

5.2 Ethical Aspects

The use of deep learning for disease detection in apple leaves raises several ethical considerations.

Firstly, the use of deep learning algorithms relies on the availability of a large amount of data. The data used to train these models should be collected ethically, with the informed consent of the individuals or organizations providing the data. Additionally, the data should be protected against unauthorized access and breaches, to protect the privacy of the individuals or organizations involved.

Secondly, the use of deep learning algorithms can lead to the automation of decision making, which raises concerns about bias and discrimination. These algorithms may inadvertently perpetuate or amplify existing biases in the data, leading to unfair or discriminatory outcomes. Therefore, it is important to ensure that these algorithms are transparent, interpretable, and fair, and that any bias present in the data is identified and addressed.

Thirdly, as the use of deep learning for disease detection in apple leaves could lead to a reduction in the use of chemical pesticides, it is important to consider the potential impact on farmers and farm workers who may rely on those chemicals for their livelihoods. Alternatives should be provided to ensure that these farmers and workers are not left worse off.

Lastly, it is important to consider the impact of the technology on the environment. The use of deep learning for disease detection in apple leaves can lead to more sustainable and organic farming practices, however, it is important to consider the energy consumption, data storage and other environmental aspects of the technology.

5.3 Sustainability Plan

sustainability plan for the use of deep learning for disease detection in apple leaves should include the following key elements:

Energy Efficiency: Implement strategies to minimize the energy consumption of the deep learning algorithms, such as using more efficient hardware and cloud-based computing resources.

Data Management: Ensure that data is collected, stored, and processed in an ethical and sustainable manner. This includes protecting personal information, minimizing data waste and encouraging data reuse.

Fairness and Transparency: Ensure that the deep learning algorithms are transparent, interpretable, and fair, and that any bias present in the data is identified and addressed.

Alternative livelihoods: Develop and implement alternative livelihoods for farmers and farm workers who may rely on chemical pesticides for their livelihoods, in order to ensure that the farmers and workers are not left worse off.

Environmental impact: Minimize the environmental impact of the technology by using renewable energy sources, reducing carbon footprint and implementing strategies for reducing waste.

Continual improvement: Continuously monitor and evaluate the performance and impact of the deep learning algorithms, and make adjustments as necessary to ensure that the technology remains sustainable and ethical.

Community involvement: Engage with the community, including farmers and other stakeholders, to ensure that their needs and concerns are taken into account when implementing the technology."

CHAPTER 6

CONCLUSION

6.1 Summary of the Study

We established this conservative think tank to research into apple leaf diseases in an effort to aid ranchers in raising yields and profits. The finding suggests how well our modified CNN responded and how it correctly identified the wrong leaf image. For our analysis, we obtained four different sickness photos and preprocessed them. The information preprocessing choices were then cautiously put into practice with the intention of making them ideal for the applied set of guidelines. Data collectors must be set up so that they can accurately reflect the facts. In our investigations, one informational installment is finished at the same moment the alternative is put to the test.

6.2 Conclusions

In conclusion, deep learning approaches have been shown to be effective in detecting diseases in apple leaves. The results of our study demonstrate the potential of using convolutional neural networks for identifying and classifying various diseases with high accuracy. However, there is still room for improvement, and further research should be conducted to optimize the performance of these methods. The implementation of deep learning for disease detection in apple leaves can greatly aid in the early detection and prevention of plant diseases, ultimately benefiting the apple industry. Overall, the use of deep learning in this field is promising and holds great potential for future applications.

6.3 Implication for Further Study

Further studies should be conducted to improve the performance of deep learning approaches for disease detection in apple leaves. This can include incorporating more diverse data sets, exploring different architectures and pre-processing techniques, and implementing methods for real-time detection in orchards. Additionally, research can be conducted on the feasibility of using these methods for disease detection in other types of plants. Overall, continued development and refinement of deep learning approaches has the potential to greatly aid in the early detection and prevention of plant diseases. When attaching identical strategies to these depictions of the Leaf Disorder, a range of interpretations could be made, including:

1. This study might also be applicable to user-friendly mobile software or web development.
2. This thesis may be expanded to include additional types of diseases.
3. Extra datasets may be facilitated with this thesis in terms of enhancing the insights.

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