SUGARCANE PLANT DISEASE DETECTION USING TRANSFER LEARNING

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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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DHAKA, BANGLADESH

SEPTEMBER 2022

APPROVAL

This Project titled "**Sugarcane Plant Disease Detection Using Transfer Learning**", submitted by Asha Mou Basak, ID No-181-15-10814 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **12 September, 2022**.

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We hereby declare that, this project has been done by us under the supervision of **Ahmed Al Marouf, Lecturer (Senior Scale), Department of CSE,** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ACKNOWLEDGEMENT

First I express our heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final year project/internship successfully.

I really grateful and wish my profound my indebtedness to **Mr. Ahmed Al Marouf, Sr. Lecturer**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Deep Learning*" to carry out this project. His endless patience ,scholarly guidance ,continual encouragement , constant and energetic supervision, constructive criticism , valuable advice ,reading many inferior draft and correcting them at all stage have made it possible to complete this project.

I would like to express our heartiest gratitude to **Dr. Touhid Bhuiyan, Head,** Department of CSE, for his kind help to finish our project and also to other faculty member and the staff of CSE department of Daffodil International University.

I would like to thank our entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, I must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

Sugarcane farming is the well-organized type of farming. Sugar and ethanol are produced mostly from sugarcane. We know, Bangladesh is an agricultural country, and agriculture is the backbone of the Bangladeshi economy. Plant diseases are the cause of significant economic losses in the agriculture business around the world and for Bangladesh purpose sugarcane plant disease is one of them. It is one of our farmers' most well-known issues. This study involves numerous plant diseases in order to discover a remedy and better strategies to reduce them. The dataset consists of images of healthy as well as diseases of sugarcane plants. For this research nearly 2000 images have been collected. In this study, transfer learning based popular image classifiers, such as, ResNet50, VGG19, and InceptionV3 were considered which aid in the classification and detection of illness images. Among those classifiers, ResNet50 outperformed the other two algorithms with an accuracy of 99.75% on test set.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

One of the most valued crops is sugarcane, grown in tropical and subtropical climates. This is the primary source of sugar, a versatile and indispensable functional element in food that also contributes to the sweetness of dishes. The most significant among these are that added sugar in foods acts as a sweetener, preservative, texture modifier, fermentation substrate, coloring and flavoring agent, bulking agent [1]. On the other hand, sugarcane juice is the most popular drink in all over the world. Bioethanol and power are also produced from sugarcane. Sugarcane is grown in almost every country and is a crucial crop for many of them. In Bangladesh, sugarcane is the most important cash crop. Stick production is estimated to be over 5.5 million tons per year [2]. Around 0.38 million acres of land in Bangladesh are planted with sugarcane. Though sugarcane is grown in almost all of the country's provinces, the most developed are Chittagong, Comilla, Sylhet, Dhaka, Faridpur, Jamalpur, Kishoreganj, Tangail, Jessore, Kushtia, Bogra, Dinajpur, Pabna, Rajshahi, and Rangpur. Sugarcane diseases are the major concern for ranchers and a threat to their livelihood. The economy will suffer if the cultivation of these plants decreases. During its growth period, it is afflicted with a number of ailments. Among many red rot, borer, wilt, rust, smut, pineapple disease, and chlorosis are the most common illnesses. Here main focuses are - (1) Red rot, (2) Borer, (3) Rust, (4) Wilt, and (5) Healthy sugarcane in this research. The dataset consists of two classes of sugarcane pictures, which are diseased and healthy. The ability to detect and diagnose sugarcane illnesses has played a critical role in making them inevitable. I will use Transfer Learning (TL) with some algorithms that are - ResNet50, VGG19, and InceptionV3 to classify and detect diseases in this study. Because of its great accuracy, Transfer learning (TL) is concerned with the storage of knowledge obtained while resolving one problem and its subsequent application to another similar but unrelated problem in deep learning. Only general model features that were learned from the initial task can be used for transfer learning in deep learning. As the trained model for feature extraction for Transfer Learning, the ResNet50 deep learning model is being employed. VGG19 is a sophisticated CNN with pre-trained layers and a keen understanding of how shape, color, and structure create an image. The Inception V3 model employed a number of network optimization approaches for improved model adaption.

1.2 Motivation

The most well-known difficulty for our farmers in Bangladesh is sugarcane plant disease. In Bangladesh, sugar production currently accounts for only about 5% of total interest. Jiggery production, which is mostly made from sugarcane, accounts for around 20% of interest, while importation accounts for the remaining 75% [3].But sadly, every year, our country's farmers lose money owing to sugarcane infections. As a result, sugarcane production is dropping, and the government is forced to import sugar from other countries. Even if many initiatives have been taken previously, they are insufficient and many aspects still need to be improved. These have motivated us to work on transfer learning and disease detection so that we can assist our farmers in growing more sugarcane. Not a lot of work is shown in this area still now. That is why this is intended to use a transfer learning algorithm to detect sugarcane illness.

1.3 Rationale of the Study

I have some fantastic ideas for this study, but I may not be able to complete all of my thoughts and objectives within the time frame allotted. At this time, contemporary technology may be found almost wherever. As a result, the primary goal of my research is to identify and classify sugarcane illnesses.

Transfer learning (TL) is a deep learning technology that works mainly when there is insufficient data to complete the task and the data are connected. Plant diseases are detected and classified using TL algorithms. We decided to adopt the Transfer learning (TL) based models to approach of deep learning as a result of all of this. Practically speaking, leveraging or transferring knowledge from previously learned tasks for the learning of new tasks has the potential to greatly increase a reinforcement learning agent's sampling efficiency.

1.4 Research Questions

- ❖ RQ-1: Is it possible to identify sugarcane plant diseases?
- ❖ RQ-2: Is this research going to be able to detect sugarcane plant diseases?
- ❖ RQ-3: What method will be used to detect disorders in this research?
- ❖ RQ-4: Should we apply transfer learning in the right way?
- ❖ RQ-5: What kinds of information will be gathered?
- ❖ RQ-6: Will be the TL based algorithms effective for plant diseases?
- ❖ RQ-7: What sources do we use to gather data?
- ❖ RQ-8: Will the findings of this study be accurate?
- ❖ RQ-9: Does the research have any limitation?
- ❖ RQ-10: What will be the future progress of this research?

1.5 Expected Outcome

We anticipate that this study will aid farmers in detecting sugarcane diseases. With this technique, (1) Farmers can quickly identify infections, (2) Sugarcane production grows, (3) Benefiting is the agricultural industry, (4) Sugarcane illnesses will be less prevalent as a result of this, (5) Transfer learning, other algorithms and its techniques for detecting diseases are becoming more well-known, (6) For detecting sugarcane plant diseases, current or novel deep learning algorithms can be used effectively, (7) Develop an application that is simple for farmers to use.

1.6 Project Management and Finance

We gathered sugarcane photographs from a prior student of our university for our research project. It was quite difficult for us to manage our dataset in this COVID-19 condition as it is not fully normal yet. We didn't have to spend any money on this endeavor because we didn't need to buy anything. To put our research together, we read a lot of related papers and articles. Then we put our research project into action. We'll illustrate how long it took to handle the project in this area. The following table shows the time spent on our research endeavor as measured in hours.

TABLE 1.6.1: PROJECT MANAGEMENT TABLE

Work	Time Duration
Data Collection	4 Months
Papers and Articles Review	3 Months
Experimental Setup	1 Month
Implementation and Validation	4 Months
Report Writing and Documentation	2 Months
Total	12 Months

1.7 Report Layout

- Chapter 1 has the introduction part of the thesis with its motivation, rationale of the study, research questions, expected outcome and project management and finance.
- Chapter 2 discusses preliminaries, related works, research summary analysis, the scope of the problem, and challenges.
- Chapter 3 contains the workflow of this research, data collection procedure, and statistical analysis, applied mechanism and feature implementation.
- Chapter 4 covers experimental evaluation and some relevant discussions, the outcome of research via numerically and graphically.
- Chapter 5 explains this research impact on society, environment and plan.
- Chapter 6 provides a summary of this research work summary and future work.

CHAPTER 2
BACKGROUND

2.1 Terminologies

As diseases of the sugarcane crop are a worldwide issue, sugarcane production is decreasing day by day. It was not a huge issue when such diseases first appeared. However, it is currently having a negative impact on the economy. Farmers have a difficult time identifying certain diseases. For this, many researchers study on those disorders and employ a variety of techniques. They were also effective in using those methods and publishing a number of papers as a result. Machine learning methodologies, deep learning methods, image processing, Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Support Vector Machine (SVM) and some others are the methods which are applied by researchers for publishing papers. We will devise a strategy for fixing the problem under this scenario. And we are going to use ResNet-50, VGG19 and InceptionV3 along with Transfer Learning (TL) which are the fundamental deep learning methods. We'll look into other similar research and work on these issues in order to get better results.

2.2 Related Works

The first step in determining the type of sugarcane disease is to determine the crop species. This research paper's literature review section will introduce past related efforts on plant disease detection and classification done by some researchers. We looked at their research to understand the processes and methodologies they used.

The model for Sugarcane Disease Detection presented by Prince Kumar et al. [4] is based on deep learning approaches. They used 4500 sugarcane photographs. They use many approaches to detect the sickness. In their research, they used Convolutional Neural Networks (CNN), YOLO, and Faster-RCNN algorithms. Their highest level of accuracy is 93.20 percent.

Arpan Kumar et al. [5] suggested an image processing-based model for Sugarcane Disease Detection and Classification. Their model recognizes image processing disease methods. K-means clustering, Gray level Concurrence matrix (GLCM), and Support vector machine (SVM) algorithms were employed in this study. They had a 97 percent accuracy rate.

Convolutional Neural Networks (CNN) was utilized by Sammy V. Militante et al. [6] to detect Sugarcane Disease using deep learning approaches. They looked at 13,842 photos of sugarcane to see if they could spot the disease. Their approaches identify and recognize the sickness. The CNN algorithm was utilized. They completed their work with a 95% accuracy rate.

Plant Leaf Detection and Disease Recognition Using Deep Learning has been worked on by Sammy V. Militante et al. [7]. Plants such as potato, tomato, apple, sugarcane, grapes, and corn were among the crops they worked on. They constructed a system that could identify and recognize different plant kinds as well as various plant illnesses. They used Convolutional Neural Networks (CNN), which were previously used for disease categorization and detection. 35,000 photos of potato, apple, tomato, maize, sugarcane, and grapes were collected. They attained 96.5 percent accuracy using the CNN approach.

Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks was developed by PENG JIANG et al. [8]. The apple leaf infection dataset (ALDD) was used in this study, which is made up of photos from research facilities and complicated photographs taken in real-world situations. Convolutional Neural Networks (CNN) were employed in this study, which included the GoogLeNet Inception structure with Rainbow concatenation. They analyzed 26,377 photos and were able to identify the apple leaf illnesses. They discovered a 78.80 percent accuracy rate.

Tomato Leaf Disease Detection Using Deep Learning Technique has been proposed by Muhammad E.H. Chowdhury et al. [9].They worked on a total of 18,162 tomato photos. Convolutional Neural Networks (CNN) are a type of deep learning method that they used here. To categorize and detect the disorders, they used Inception V3, Resnet18, MobileNet, and Desnet 201 approaches. The accuracy of the Inception V3 model was 99.2 percent. The accuracy of DenseNet201 was found to be 98.05 percent.

Dor Oppenheim et al. [10] used deep learning to develop Image-Based Potato Tuber Disease Detection. Under uncontrolled lighting circumstances, they used quicker R-CNN and low-cost RGB sensors. They used those methods on around 2,465 potato pictures. They discovered that the best accuracy was 97.1 percent and the lowest was 92.56 percent.

Shivani Sood et al. [11] worked on implementing and analyzing deep learning models for wheat rust disease diagnosis. There were 876 photos in their datasets. They employed the Convolutional Neural Networks (CNN) based models ResNet50 and VGG16. Using the VGG16 model, they were able to attain 99.07 percent accuracy.

UDAY PRATAP SINGH et al. [12] proposed a model for the classification of mango leaves infected with anthracnose disease using a Multilayer Convolution Neural Network. Mango leaves were photographed in 2,200 different ways. SVM, Particle Swarm Optimization (PSO), and Radial Basis Function Neural Network (RBFNN) techniques were used. The proposed models have a 97.13 percent accuracy rating.

2.3 Comparative Analysis and Summary

There has been some previous work using a deep learning algorithm and image processing to detect and classify various plant diseases. With the application of deep learning and image processing methods for rice disease detection, tomato disease detection, mango disease detection, potato disease detection, and other plant disease detection, the usage of deep learning and image processing methods has extended. To detect any model, various algorithms such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Artificial Neural Networks (ANN), Support Vector Machine (SVM), K-means cluster, Decision tree, Particle Swarm Optimization (PSO), and others are used at random. Transfer or inductive learning is a supervised learning strategy that applies portions of a previously trained model to a new network that is charged with solving a distinct but related problem.

TABLE 2.3.1: SUMMARY OF RELATED RESEARCH WORK.

SL	Author Name	Methodology	Description	Outcome
01.	Arpan Kumar, Anamika Tiwari	K-means cluster algorithm, Gray level Concurrence matrix(GLCM) algorithm and Support vector machine (SVM) algorithm	Detection of Sugarcane Disease and Classification using Image Processing	97%
02.	Sammy V. Militante, Bobby D. Gerardo, Ruji P. Medina	Convolutional Neural Networks (CNN)	Sugarcane Disease Recognition using Deep Learning	95%
03.	Prince Kumar, Mayank	Convolutional Neural Networks	Research Paper On Sugarcane Disease	93.20%

	Sonker and Vikash	(CNN), YOLO and Faster-RCNN algorithms	Detection Model	
04.	Dor Oppenheim, Guy Shani, Orly Erlich and Leah Tsror.	Faster R-CNN and low cost RGB sensors	Using Deep Learning for Image-Based Potato Tuber Disease Detection	97.1%
05.	Sammy V. Militante, Bobby D. Gerardo, Nanette V. Dionisio	Convolutional Neural Networks (CNN)	Plant Leaf Detection and Disease Recognition using Deep Learning	96.5%
06.	Peng Jiang , Yuehan Chen, Bin Liu, Dongjian He and Chunquan Liang	Convolutional Neural Networks (CNN),GoogLeNet Inception structure and Rainbow concatenation	Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks	78.80%
07.	Muhammad E.H. Chowdhury, Tawsifur Rahman, Amith Khandakar, Nabil Ibtehaz, Aftab Ullah Khan, Muhammad Salman Khan, Nasser Al-Emadi, Mamun Bin Ibne Reaz, Mohammad Tariqul Islam and Sawal Hamid Md. Ali	Inception V3, Resnet18, MobileNet and Desnet 201 techniques	Tomato Leaf Disease Detection Using Deep Learning Technique	Inception V3 accuracy 99.2%, DenseNet201 found 98.05% accuracy.
08.	Shivani Sood, Harjeet Singh	ResNet50 and VGG16	An implementation and analysis of deep learning models for the detection of wheat rust disease	99.07%
09.	Uday Pratap Singh , Siddharth Singh	Support Vector Machine (SVM), Parti-	Multilayer Convolutional Neural Network for the	97.13%

	Chouhan ,(Student Member, IEEE), Sukirty Jain , and Sanjeev Jain	cle swarm optimization (PSO) and Radial basis function neural network (RBFNN) algorithms	Classification of Mango Leaves Infected by Anthracnose Disease	
10.	Our proposed model	ResNet-50, VGG19, InceptionV3	Sugarcane Plant Disease Detection Using Transfer Learning	99.75%

2.4 Scope of the Problem

The goal of this research is to use transfer learning and some other algorithms to recognize and classify objects. The sugarcane plant is vulnerable to a variety of diseases. Red rot, wilt, grassy sprout, smut, leaf scald disease, red striped disease, mosaic disease, rust, borer, and other diseases are the most prevalent. Bacterial, viral, and fungal infections are caused by these diseases and have spread throughout the farmers' land. We will deal here with four different disorders. Such as- Red Rot, Borer, Rust, and Wilt. We'll talk about the diseases we use in our research in this portion.

Red Rot: Glomerella tucumanensis is the fungus that causes red rot illness. It is one of the most dangerous illnesses that can affect sugarcane. In addition, it changes the color of leaf from green to orange, then orange to yellow. The leaves are then dried from bottom to top. Internal tissues are also damaged, as are intermingled transverse white patches. It is primarily caused by high temperatures, pollution, and a greater relative humidity.

Borer: Sugarcane borer is a common concern for sugarcane growers. The larva of a pyramid moth that bores through sugarcane is known as the sugarcane borer. It also attacks the stick stalks when there isn't enough rain for a long time.

Wilt: It is the most common sugarcane disease. It is seen in canes that are 4-5 months old. Sugarcane plants become stunted as a result of the disease, with yellowing and withering of the top leaves. It's also a fungal infection.

Rust: It is yet another big issue with sugarcane. It is brought on by a fungus. Rust in sugarcane crops that spreads swiftly. It takes place in the spring and early summer. Sugarcane leaves get spots as a result of it. Spots come in a variety of colors, including black, white, orange, brown, and yellow.

2.5 Challenges

We're having a lot of trouble gathering our data. So, the collection of photographs of sugarcane for our dataset is one of the most difficult aspects of our research. It was even more difficult for us in this epidemic circumstance. When we got the photos from a former student at our university. However, conversing with him throughout the Covid-19 phase was really tough. It was also tough for us to manage the dataset, and it was difficult to separate the dataset photos. Overall, the preparation of several layers with varying epoch sizes took a lengthy time in our machine. In Google colab, we occasionally encountered an error while epochs were running and not properly executing. We have no prior knowledge of Google Colab or its setup. As a result, we had to read a lot in order to address this difficulty. We worked hard to fix our issues and kept ourselves motivated. Our supervisor was also really helpful. Finally, we kept working and obtained better outcomes.

CHAPTER- 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

The goal of this research is to diagnose sugarcane disease so that farmers can profit. To accomplish so, we gather numerous photographs of the impact of sugarcane from the farmer's sugarcane field and attempt to gain a thorough understanding of the diseases. This was accomplished through the application of transfer learning. For implementing TL well, we have used here ResNet-50, VGG19 and InceptionV3 –such the powerful and time consuming methods for image processing that we used in this project. We've worked on four different forms of sugarcane diseases here. Prior to deployment, we classified our image data into four categories based on the disease. For the ResNet-50, VGG19 and InceptionV3 algorithm, we calculated the accuracy, plot accuracy, plot loss, and loss value. Our model has a high level of accuracy.

3.2 Data Collection Process

We found data collection to be quite difficult in the case of COVID-19. A senior student of our university worked before with this topic. After this, we discussed the dataset with him. He assisted us in gathering the facts and then to aid our investigation, he helped us his collection of photographs. He provided us with over 2000 photos of sugarcane. We have collected a great deal more data from agricultural researchers who have worked with sugarcane and sugarcane-related crops. For this, we can work more easily in our research works. Moreover, we can learn about the diseases caused by sugarcane from their works. In our dataset, not all of the images depict sick crops, also some healthy pictures of sugarcane plants we have. Here, Red rot, Rust, Borer and Wilt- are the four sugarcane plant disease we have researched for. Some demo are shown below-

Red rot

In figure 3.2.1 we can see the sugarcane crops with symptoms of Red Rot Disease

Figure 3.2.1: Red Ro

Figure 3.2.1: Red Rot

Rust

In figure 3.2.2 we can see the sugarcane crops with symptoms of Rust Disease

Figure 3.2.2: Rust

Figure 3.2.2: Rust

Borer

In figure 3.2.3 we can see the sugarcane crops with symptoms of Borer Disease

Figure 3.2.3: Borer

Wilt

In figure 3.2.4 we can see the sugarcane crops with symptoms of Wilt Disease

Figure 3.2.4: Wilt

Figure 3.2.4: Wilt

Healthy

In figure 3.2.5 we've also included Healthy sugarcane images

Figure 3.2.5: Healthy Sugarcane

Figure 3.2.5: Healthy Sugarcane

3.3 Statistical Analysis

In this study on ResNet-50, VGG19 and InceptionV3 based on transfer learning, all data sets were used correctly. Statistical modeling is the process of determining the link between test and train data in order to make predictions. The statistical review of transfer learning together with a presentation on faith testing, demonstrating statistical links on transfer learning's concealed implications. Total 2212 picture of sugarcane we have collected as our dataset. But, after augmentation we have got total number of dataset is 3225 images nearly where train dataset of 2418 images and the other remaining 807 photos were taken for testing. The dataset has the ratio of 75% and 25% serially for train and test dataset. The image data set has two types of models: test models and train models. A sub model can be found in all of the healthy and illness photos. The class contains Statistical in order to discover an accurate and correct solution to the problem.

3.4 Proposed Methodology

The total number of hours worked Using ResNet-50, VGG19 and InceptionV3 as a transfer learning algorithm, create a copy for sugarcane sickness. It's explained in great detail here. The entire system is broken down into many key processes, beginning with the assignment of photos to the classification system using deep neural networks. In Figure 3.4.1, a flow diagram depicts the process of our work. Which can be used to determine whether or not sugarcane is infected.

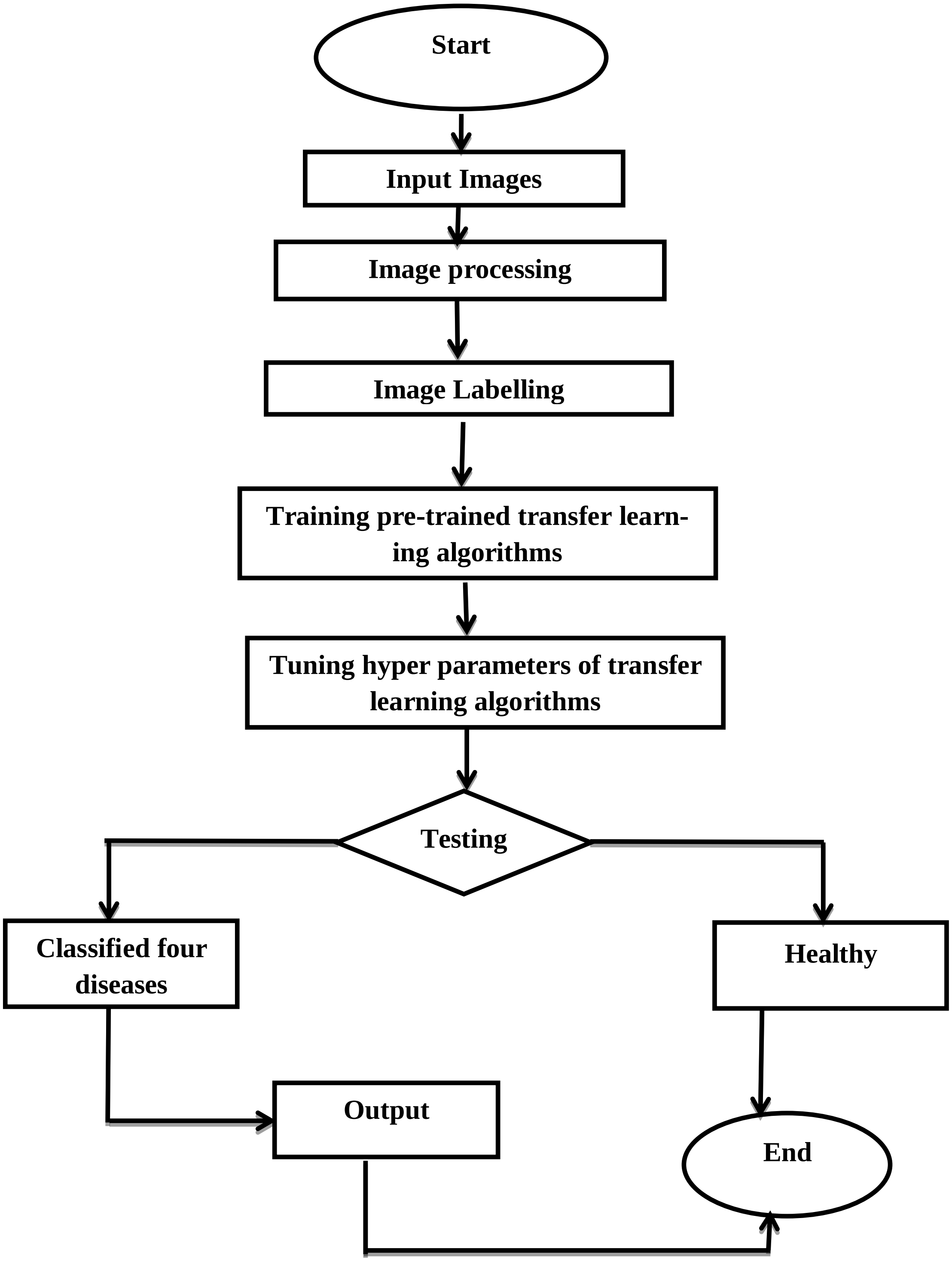


Figure 3.4.1: Prediction model Workflow diagram

Image Preprocessing and labeling:

The term "Image Pre-processing" refers to a method performed on images with the least amount of reflection. If entropy is a data measure, these behaviors do not increase picture data content, but they do decrease it. The goal of pre-processing is to improve the image information in such a way that it prevents unwanted mutilations or enhances certain image highlights that are vital for extra handling and investigation duties. Splendor adjustments change the brilliance of pixels, and the change is based on the qualities of the pixels themselves. Contrast enhancement is an important aspect of image processing. We have also used image segmentation technique for image preprocessing. In the addition, for picture preprocessing, we employed the image segmentation technique. To shorten the training time, we resize the image to 224*224 pixels. Here, we validated that all of the images' content material wished for typical learning. To split the data by disease name, we solicited the expertise of sugarcane and sugarcane crop researchers. Without this, we also deleted the duplicated and unnecessary images from the database. For healthy photos, the image data has been categorized independently. This is not fully included with disease pictures pf sugarcane plants.

Resnet-50:

We used the ResNet-50 technique to separate the problem leaves from the healthy leaves. We must first prepare the data for its training. All of the images in the Resnet-50 training dataset have been in the same size. We used 1766 photos for training in our dataset along with five classes. We made all of our photos 224 * 224 for our dataset. There is no cross-over between the classes because they are fundamentally unrelated. The dataset is normalized. Pictures are supposed to prepare for organization during Transfer Learning side by side resnet-50 preparation. Photographs are being prepared in this segment, where we used pictures in various disease classes. For the training process firstly we have to import all the necessary libraries. Then have to bring in the needed dataset. We will divide our image data into training and validation sets. Our model will be trained on the training subset at the beginning of each epoch, and at the end of each epoch, it will test its performance on the validation data. After that, visualization is needed for the training process. Here is where transfer learning truly shines. We can choose any of the cutting-edge models from the Keras applications and apply it to our situation. ResNet-50 will be the model we utilize for the time being, but the same process may be used to any other model. Transfer learning accurately saves us enormous amounts of time, space, and computing complexity in that manner. The following step is to evaluate your model after it has been trained. The train and validation accuracy with regard to each epoch then can be plotted using the matplotlib tool for the model evaluation. From this we should have a plot. For the time being, we will go on to the final stage of using our model to make predictions if the validation accuracy is sufficient. To generate predictions on any image, all we need to do is conduct a few pre-processing procedures to make sure the image's dimensions match those of the training image. For this, we can employ the opencv library. We were able to understand the value of transfer learning and how to train cutting-edge deep learning models on our unique data set.

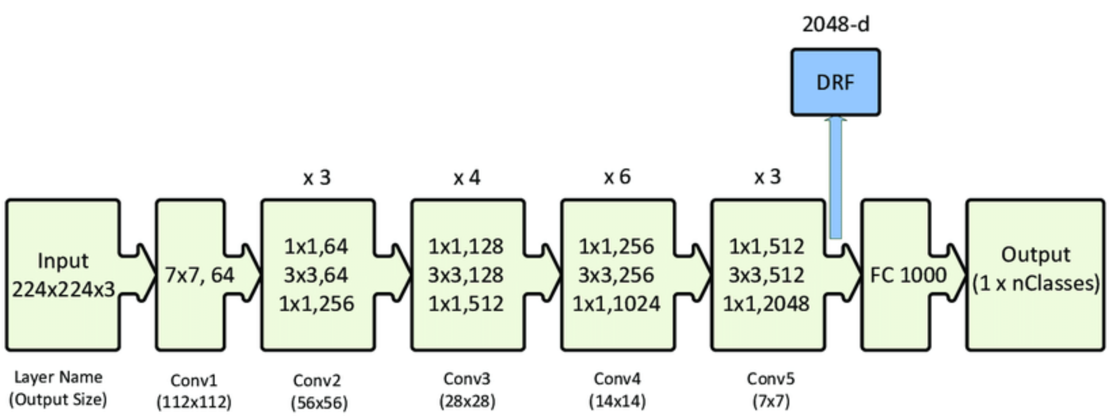


Figure 3.4.2: ResNet-50 process

VGG19:

Along with resnet-50 we have used VGG19 in this research for detecting separately the disease images from healthy images using various layers and processes. The input image for the VGG19 model is a 224 224 image with 3 channels, each with its mean RGB value removed. The model comprises 19 weighted layers made up of 16 convolutional layers and 3 fully connected (fc) layers. Each block in the VGG architecture is made up of layers for 2D Convolution and Max Pooling. However, by including a convolutional layer in the final three blocks, the network's depth has been further improved. For VGG19, Keras has a dedicated preprocessing function along from other VGG model. For the training process we have to first retrieve the resources and completing this we need to get the pre-trained net. Then as the parts of basic usage we have to classify images, obtain a list of the expected entity's properties that are accessible, Identify the ten most likely entities predicted by the net and calculate their probability. By this, a non-ImageNet class object will not be correctly detected. Then have to obtain the names of all the classes that are offered. In order for the trained network to produce a vector representation of an image, get removed the final three layers of the network and have a set of image and Put a group of images' characteristics into visual form.

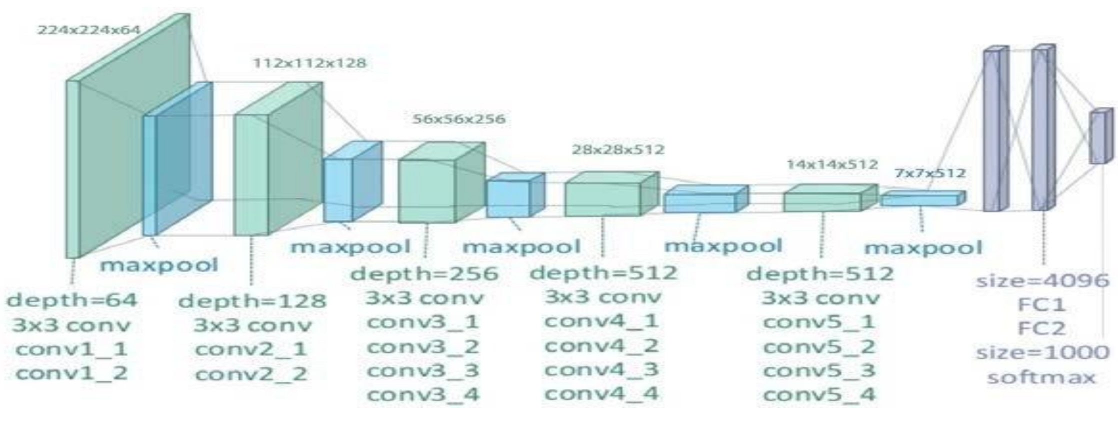


Figure 3.4.3: VGG19 process

In the training net, we will extract the weights of the first convolutional layer. After this, have to create a classifier using the pre-trained mode and a test set and training set. The pre-trained net's linear layer should be removed. We should make a new net with the pre-trained net at the top, followed by linear layers, and softmax layers. On the test set, if flawless accuracy is achieved, check the total amount of parameters for every array on the internet. Get the complete list of the parameters. Then have to get the complete list of the parameters, the layers type counts and a summary image should be shown. And finally we can export the net into required internet site like MXNet.

InceptionV3:

The last but not the least algorithm has been used here is the InceptionV3 model. The model is the result of numerous concepts that have been established by various researchers over the years. Convolutions, average pooling, max pooling, concatenations, dropouts, and fully linked layers are just a few of the symmetric and asymmetric building elements that make up the model. Inputs for activation are subjected to batch normalization, which is utilized widely across the model. To calculate loss, softmax can be used. The model must be trained using a sizable collection of labeled photos before it can be used to recognize images. The datasets for training and evaluating are kept apart on purpose. Only photos from the training dataset and the evaluation dataset are utilized to train the model and assess model accuracy, respectively. Data is retrieved from the file system or local memory by hosts, which then perform any necessary data preprocessing before sending the prepared data to the TPU cores. We refer to these three stages of data handling carried out by the host independently as: Storage is followed by preprocessing and transfer.

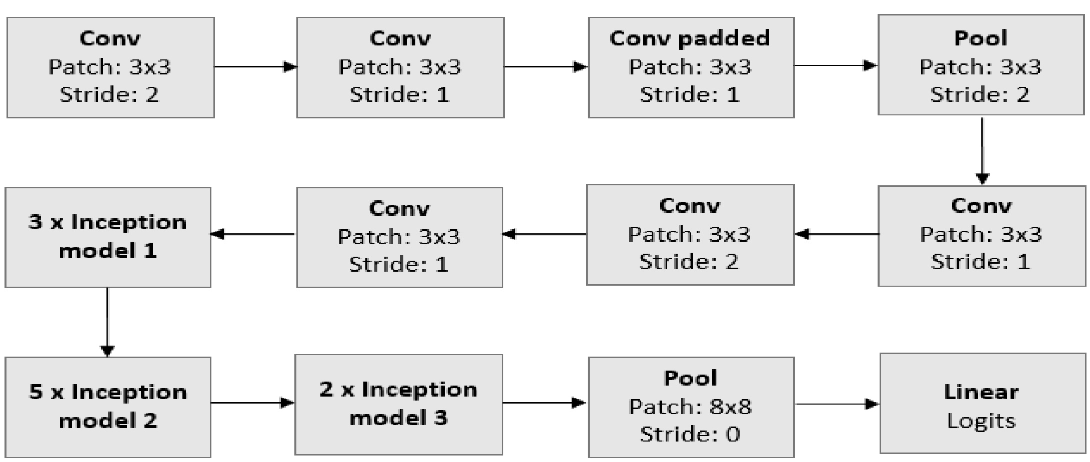


Figure 3.4.4: InceptionV3 process

The system needs to be balanced in order to produce optimal performance. Execution will be host-bound if the host CPU needs more time than the TPU to complete the three phases of data handling. Inception version 3's present configuration is almost input-bound. After being decoded and preprocessed, images are pulled from the file system. There are various preprocessing stages that range in complexity from moderate to complex. The training pipeline will be preprocessing bound if the most intricate preparation phases are used. The system's most important component, age preprocessing, can affect the model's training accuracy to the highest possible level. Images should at the very least be decoded and scaled to fit the model. But to achieve adequate accuracy, decoding and scaling alone are insufficient. The model needs to go through the training dataset multiple times to get better at recognizing images. Depending on the global batch size, it may take several epochs to train Inception v3 to a level of accuracy. Before feeding the images to the model, it is helpful to continuously modify them such that a specific image is somewhat different at each iteration. It takes both art and science to preprocess photographs in the most effective way. The recognition abilities of a model can be considerably improved by a well-designed preprocessing stage. A preprocessing step that is too straightforward could artificially cap the accuracy that the same model can achieve during training. Preprocessing choices in Inception v3 range from being very straightforward and computationally cheap to being moderately intricate and computationally expensive. Depending on whether the model is being trained or utilized for inference/evaluation, preprocessing is different. A popular method for normalizing input characteristics on models that can significantly shorten convergence time is batch normalization. By taking the mean away and dividing by the standard deviation, activation inputs are made normal. Two trainable parameters are added to each layer in order to maintain balance when back propagation is present. Training becomes increasingly challenging as batch sizes increase. Numerous methods are still being put forth to make training for large batch quantities effective.

Testing:

Testing is crucial because it allows us to determine how well our model performs. The informative index was previously created using a convolutional network approach; therefore the training data is known. The softmax classifier verifies this result image. This classifier is a loss function, which in the context of Transfer learning advises us to assess how positive or negative a given order term is in order to accurately arrange main informative things in our informational collection.

3.5 Implementation Requirements

I followed a few procedures in order to put the plan into action. To begin, I will need a dataset, which we created using a smartphone camera. To run the programs, I needed an IDE. As an IDE, I used Google Collaboratory. Because all of the components are pre-installed, Google Colaboratory is an excellent IDE. Work can begin by simply importing the required package. On Google Colab, I also configured the runtime as GPU. The testing and training components of our dataset were divided into two pieces. I primarily used "Google Colab" for data pretreatment and algorithm implementation. After that, I finished the installation and received the desirable results. Finally got the accuracy.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

For the purpose of preparing the model on the given dataset, the experiment was carried out on Google Colab. It naturally downloads all of the libraries from the internet; no libraries need to be installed remotely. It has recently become well-known for doing transfer learning, deep learning, machine learning, and computer vision projects. We used a high-end computer with a GPU for our research. On Google Colab, GPU and TPU resources are available. There are 2212 photos in our collection, which are classified into five categories. Affected photographs are divided into four groups, while healthy images are kept into one. All of the photographs have been scaled to 224 x 224 pixels. With an epoch of 10, the batch size was set to 16 and the batch size was set to 16. The epochs take a long time to finish. There was a Windows 10 operating system in use. A computer with at least 4 GB of RAM is required for creating a deep learning model; otherwise, it will not function properly. Our computer has 4 GB of RAM and a 500 GB hard drive. We conducted all of our research on our computer.

4.2 Experimental Results & Analysis

This section discusses the discoveries that have been made. Using a variety of evaluation matrices, the performance of classifier models in classifying the sugarcane pictures dataset was estimated. Sensitivity, Specificity, Precision, Recall, Accuracy, F-score, and

Confusion matrix were calculated. For this model evaluation, specific classifications must be measured.

Sensitivity: Sensitivity accurately recognizes the genuine/true positive value.

Sensitivity = True Positive / (True Positive + False Negative) × 100%

Specificity: Specificity detects the true negative value accurately.

Specificity =True Negative / (False Positive + True Negative) × 100%

Precision: Precision is defined as the ratio of the total true positives value to the entire false positives value.

Precision = True Positive / (True Positive + False Positive) × 100%

Recall: Recall is a metric that measures a classifier's ability to detect positive labels. It counts how many correct positive predictions were made out of all positive forecasts.

Recall = True Positive / (True Positive + False Negative) × 100 %

Table 4.2.1: Results of various algorithms' confusion matrices

Algorithms	***Accuracy (Test)***	***Loss (Test)***	***Precision***	***Recall***	***F1-Score***
ResNet50	**0.9975**	**0.02098**	**0.9974**	**0.9974**	**0.9974**
VGG19	0.9963	0.02264	0.9949	**0.9974**	0.9961
InceptionV3	0.9913	0.02915	0.9923	0.9897	0.9910

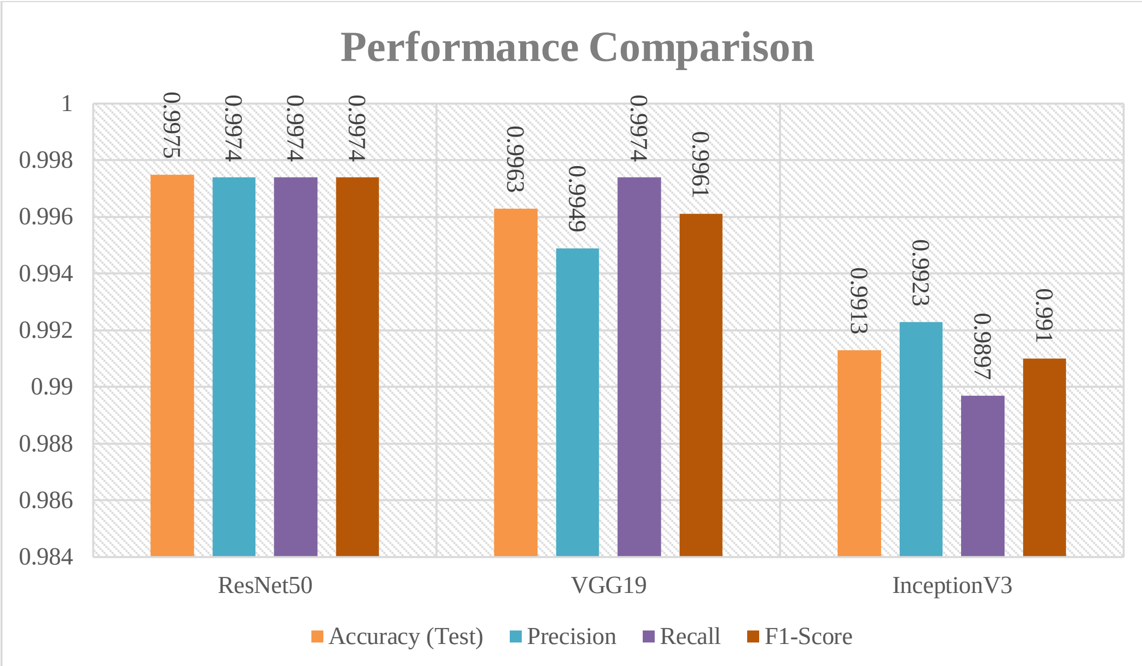


Figure 4.2.1: Performance comparison of different transfer learning algorithms

Accuracy: The total number of samples divided by the total number of true values in forecasts is the Accuracy.

Accuracy = (True Positive + True Negative) / Total Number of Samples

F1-score = the weighted average of Precision and Recall is the F1-score.

F1 score = (2 x Precision x Recall) / (Precision +Recall) ×100 %

Here, after processing all the steps we have the results of Test accuracy, Test loss, Precision, Recall, and F1score along with other results for the three algorithms. Among the three, ResNet-50 has the highest Test accuracy-99.75%, Test loss- 2.098%, Rrecision-99.74%, Recall-99.74% and F1score-99.74%. Without this, VGG19 has the same Recall as ResNet-50.

Table 4.2.2: Confusion matrix for ResNet-50 algorithm

True	**Healthy**	388 **TP**	1 **FP**
	Unhealthy	1 **FN**	417 **TN**
ResNet50		**Healthy**	**Unhealthy**
		Predicted	

Table 4.2.3: Confusion matrix for VGG19 algorithm

True	**Healthy**	387 **TP**	2 **FP**
	Unhealthy	1 **FN**	417 **TN**
VGG19		**Healthy**	**Unhealthy**
		Predicted	

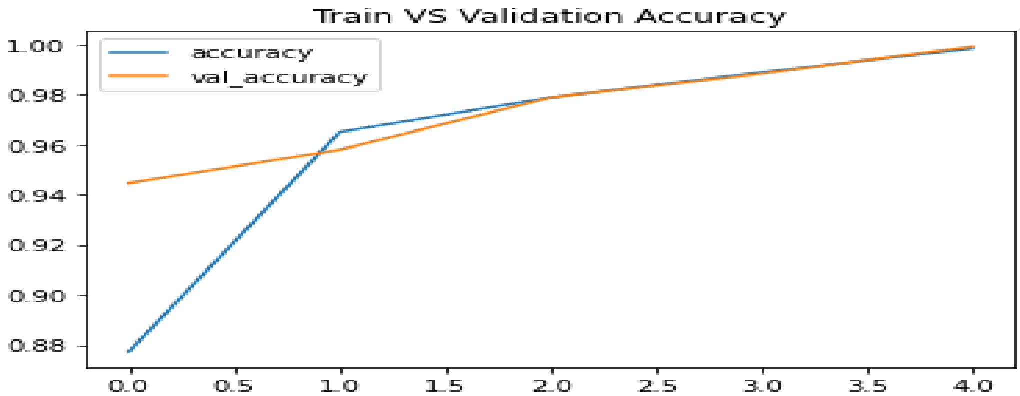
Table 4.2.4: Confusion matrix for InceptionV3 algorithm

<table>
<tr><td rowspan="2">True</td><td>Healthy</td><td>386
TP</td><td>3
FP</td></tr>
<tr><td>Unhealthy</td><td>4
FN</td><td>414
TN</td></tr>
<tr><td colspan="2" rowspan="2">InceptionV3</td><td>Healthy</td><td>Unhealthy</td></tr>
<tr><td colspan="2">Predicted</td></tr>
</table>

Both the training and testing datasets for this study have been run 5 times. 25% of our images are test sets, while the remaining 75% are training sets. Training and testing sets exhibit varying levels of accuracy and loss across all epochs. Training and testing sets exhibit varying levels of accuracy and loss across all epochs. Our final for ResNet-50 accuracy was found to be 99.75%, for VGG19 it was 99.63% and finally for InceptionV3 was 99.13%.

Table 4.2.5: Epochs Result of Train & Validation of ResNet-50

Step	**Train Accuracy**	**Train Loss**	**Validation Accuracy**	**Validation Loss**	**Test Accuracy**	**Test Loss**
1st	0.8773	1.3775	0.9446	0.2132	0.9975	0.02098
2nd	0.9650	0.2150	0.9579	0.1097	0.9975	0.02098
3rd	0.9788	0.1071	0.9788	0.0768	0.9975	0.02098
4th	0.9888	0.0858	0.9883	0.0558	0.9975	0.02098
5th	0.9983	0.0442	0.9991	0.0262	0.9975	0.02098



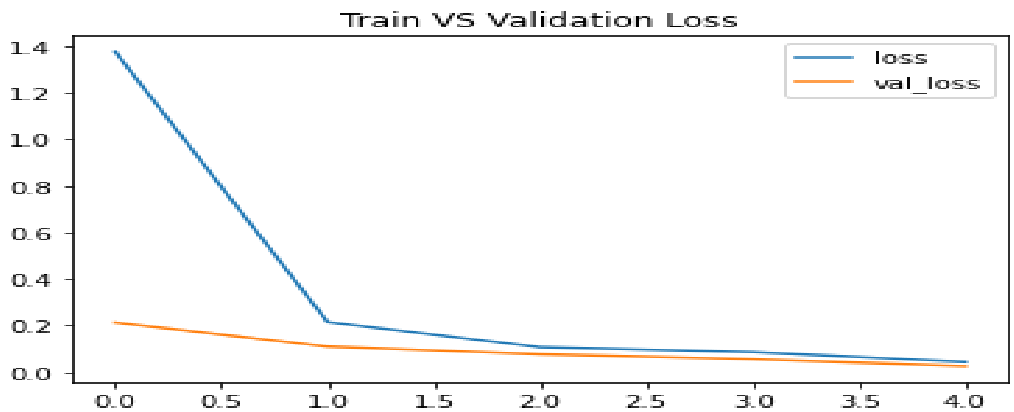


Figure 4.2.2: Train Accuracy vs Validation Accuracy and Train loss & Validation Loss of Resnet-50

Table 4.2.6: Epochs Result of Train & Validation of VGG19

Step	**Train Accuracy**	**Train Loss**	**Validation Accuracy**	**Validation Loss**	**Test Accuracy**	**Test Loss**
1st	0.8698	1.4261	0.9376	0.2231	0.9963	0.02264
2nd	0.9583	0.2357	0.9490	0.1124	0.9963	0.02264
3rd	0.9674	0.1142	0.9543	0.0834	0.9963	0.02264
4th	0.9812	0.0941	0.9612	0.0653	0.9963	0.02264
5th	0.9911	0.0519	0.9822	0.0311	0.9963	0.02264

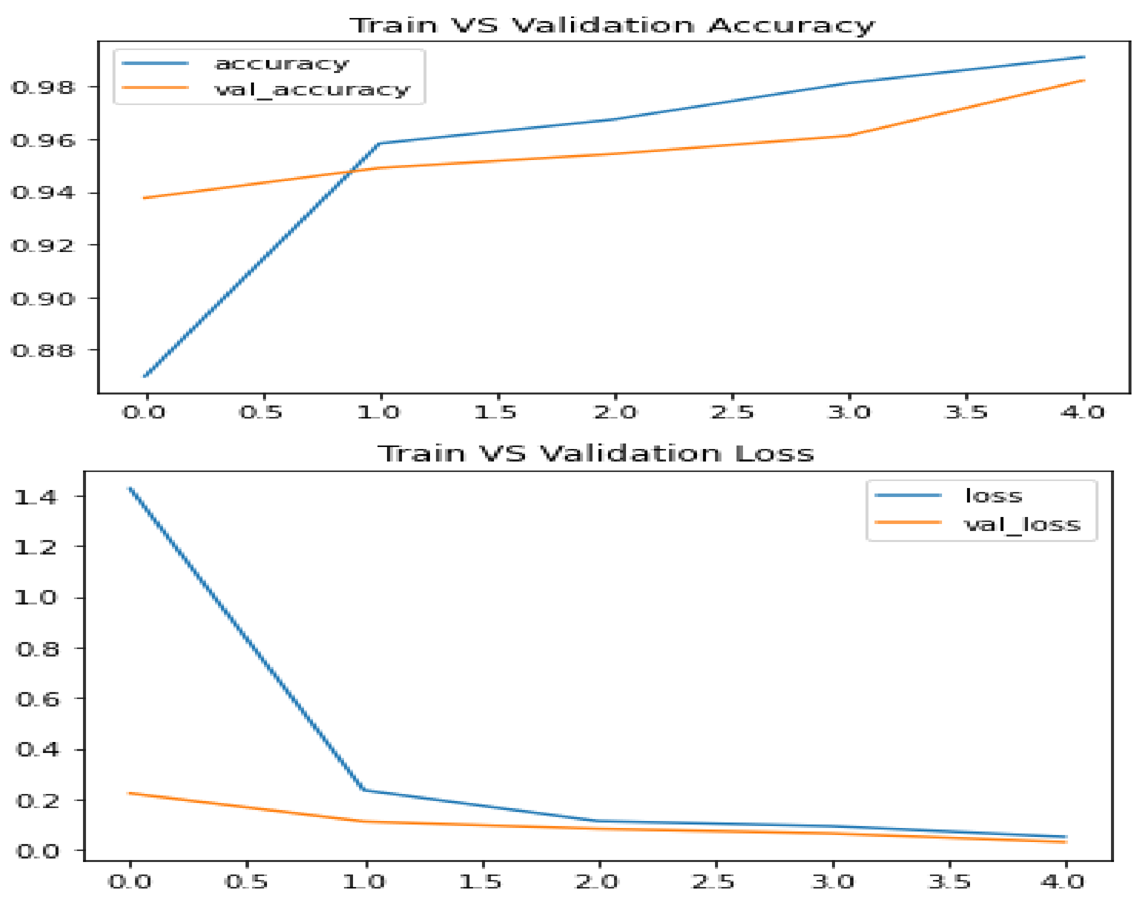
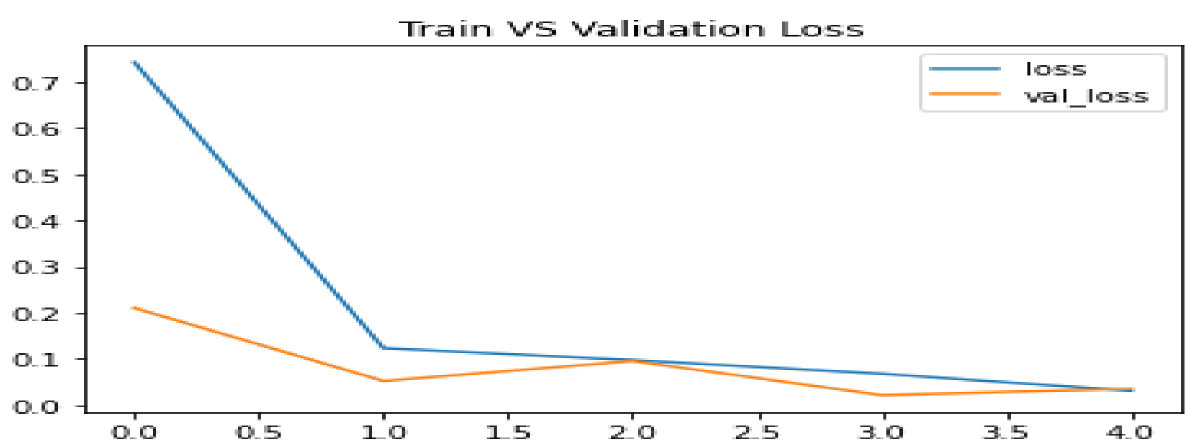


Figure 4.2.3: Train Accuracy vs Validation Accuracy and Train loss & Validation Loss for VGG19

Table 4.2.7: Epochs Result of Train & Validation of InceptionV3

Step	**Train Accuracy**	**Train Loss**	**Validation Accuracy**	**Validation Loss**	**Test Accuracy**	**Test Loss**
1st	0.8776	0.7427	0.9368	0.2101	0.9913	0.02915
2nd	0.9620	0.1230	0.9847	0.0518	0.9913	0.02915
3rd	0.9727	0.0970	0.9768	0.0949	0.9913	0.02915
4th	0.9797	0.0673	0.9946	0.0211	0.9913	0.02915
5th	0.9893	0.0306	0.9888	0.0347	0.9913	0.02915



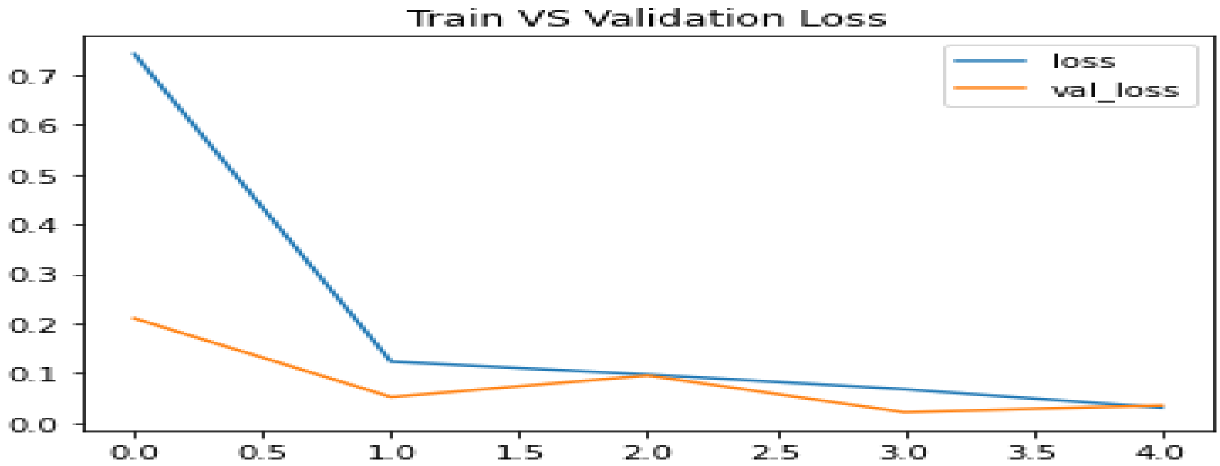


Figure 4.2.4: Train Accuracy vs Validation Accuracy and Train loss & Validation Loss for InceptionV3

4.3 Discussion

This section contains a discussion of the experimental design of our study as well as the algorithm's performance in terms of Sensitivity, Specificity, Precision, Recall, Accuracy, F-score, and confusion matrix. We have tried to run 5 epochs in our research. Every epoch, we displayed distinct training and testing dataset accuracy and loss values. Our test validation precision went up to 100%. Additionally, we talked about the plots showing the accuracy of training and validation as well as the loss of training and validation. At Google Colab, we completed our full implementation. Here, we have worked with ResNet-50, VGG19 and InceptionV3 algorithms based on Transfer Learning method. It requires a powerful computer with a GPU. After the calculation we have the result that ResNet-50 has the best accuracy of 99.75% when VGG19 and InceptionV3 have 99.63% and 99.13% serially .So, we can clearly see the conclusion of the result that InceptionV3 has the lowest with comparison to the other two algorithms.

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

In this study, we demonstrate how to recognize the diseased area of sugarcane. In our research, we used some transfer learning methods that will have a favorable impact on our society. By identifying sugarcane illness and minimizing sugarcane crop diseases, it will have an impact on society. Farmers can readily identify the sugarcane plant's sickness and take action as soon as possible from these research results. Sugarcane is an important crop in our country, but it cannot meet all of our needs. Sugar and ethanol are in high demand after main crop rice in our country. As a result, we'll have to import sugarcane from somewhere else. However, if we can use this technology to safeguard crops from numerous diseases, farmers will be able to readily identify the infections. Sugarcane productivity will increase as they become more aware of and control sugarcane illnesses. Sugarcane plantations are widely planted, and our sector generates more sugar and ethanol if we can solve the plant's disease related problems. We no longer need to import sugarcane from other countries. This will save money and will be beneficial to our society.

5.2 Impact on Environment

As previously said, we focus our research on our farmers in order to detect sugarcane illnesses. It will be extremely beneficial to our farmers. Our research endeavor will have a beneficial and bad impact on the environment. In terms of the positive influence, because many sugarcane crops will survive disease, cultivation will rise. We can also export those to earn foreign cash after our country's demand is met for our country's betterment. In terms of negative consequences, once a disease has been identified, farmers will almost certainly try to manage it by employing a variety of deadly chemicals and fertilizers that are genuinely hazardous to humans, polluting the environment. So, this has an adverse effect on the ecosystem.

5.3 Ethical Aspects

Sugarcane is a crucial crop in our country, but it cannot meet our demand in its entirety, thus we must import sugarcane from another country. However, if we can use this strategy to safeguard crops from numerous illnesses, farmers will be able to easily handle the situation, and sugarcane production will increase. Farmers who use this approach cultivate a large number of sugarcane crops. As a result, we won't need to import sugarcane from other nations, which will save us a lot of money.

5.4 Sustainability Plan

The Sustainability Plan provides us with practical suggestions for any research endeavor as well as future goals. The goal of our approach is to identify sugarcane illness. This model must be designed with the goal of identifying and classifying sugarcane illnesses. As a result, farmers can quickly identify diseases and take action against them. For this reason, sugarcane cultivation will rise at a faster rate, benefiting farmers.

CHAPTER 6

CONCLUSION, RECOMMENDATION AND FUTURE WORKS

6.1 Summary of the Study

Data collection, Data preprocessing, implementation, and assessment are all aspects of our study process. For our dataset, we first gathered photos of sugarcane. We gathered photos from a senior student at our university. He provided us with over 2212 photos of sugarcane. Moreover, in our research, we attempted to acquire more information. However, gathering so many photographs in a pandemic environment was extremely difficult. That's why we spent time with the previous student dataset. After that, we focused on data processing. We separated the data into two categories: training and testing. Then, we utilized Google Colab to put it all together. To achieve a good outcome and precision, we applied three algorithms based on a pre-determined method. The photos were detected and classified using the Resnet-50, VGG19 and InceptionV3 algorithms along with transfer learning. Finally, we used these methods to properly complete our research and obtain the highest accuracy. We are confident that the farmers will benefit much from this research. As a result of our findings, we can conclude that the ResNet-50 algorithm is the most effective for identifying and classifying plant illnesses as it has the highest accuracy rate. And we expect it will be extremely beneficial to our farmers.

6.2 Conclusion

The agricultural sector is one of the most significant in the world, as crops provide the most basic requirement for food. As a result, recognizing crop diseases is beneficial to our agricultural industries. Transfer learning method with the full form (ResNet-50), full form (VGG19) and InceptionV3 (full form) are used to detect and categorize crop illnesses. We collaborated with TL in the hopes of detecting and classifying sugarcane illnesses. It will be extremely beneficial to farmers as well as our economic industry. With this model, we were able to reach the highest accuracy of percent. As a result, this research proposes a method for farmers to use transfer learning to detect and classify sugarcane infections.

6.3 Implication for Further study

Technology has pervaded every aspect of modern life. It has made life simpler than it was previously. We hope to create an Android application in the future. Farmers can readily spot the sickness by looking at images in this way. In the future, we'd like to work with more sugarcane images as well as sugarcane diseases. New methods such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Support Vector Machine (SVM), Long Short-Term Memory (LSTM) etc. are being considered. In addition, use a variety of various methods and models. We can make our research considerably more efficient and valuable by using new methods and adding more models. We also wish to collaborate with other plants to identify and classify sickness in them.

REFERENCES

[1]The use of sugar in foods, Available at: https://pubmed.ncbi.nlm.nih.gov/3863796/ [online]

[2] Sugarcane in Bangladesh, Available at: https://en.banglapedia.org/index.php.Sugarcane / [online] [Accessed 18 june, 2021].

[3] M. S. Rahman, S. Khatun, M. k. Rahman (2016) Sugarcane and Sugar Industry in Bangladesh: An Overview.

[4] Prince Kumar, Mayank Sonker and Vikash R.P (2020). Research Paper on Sugarcane Disease Detection Model. Turkish Journal of Computer and Mathematics Education Vol.12 No.6 (2021), 5167-5174.

[5] Arpan Kumar, Anamika Tiwari, R.P. (2019). Detection of Sugarcane Disease and Classification using Image Processing. International Journal for Research in Applied Science & Engineering Technology (IJRASET). ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.177. Volume 7 Issue V, May 2019

[6] Militante, Sammy V.; Gerardo, Bobby D.; Medina, Ruji P. (2019). *[IEEE 2019 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE) - Yunlin, Taiwan (2019.10.3-2019.10.6)] 2019 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE) - Sugarcane Disease Recognition using Deep Learning. , (), 575–578.*

[7] Militante, Sammy V.; Gerardo, Bobby D.; Dionisio, Nanette V. (2019). *[IEEE 2019 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE) - Yunlin, Taiwan (2019.10.3-2019.10.6)] 2019 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE) - Plant Leaf Detection and Disease Recognition using Deep Learning. , (), 579–582.*

[8] Jiang, Peng; Chen, Yuehan; Liu, Bin; He, Dongjian; Liang, Chunquan (2019). *Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks. IEEE Access, 7(), 59069–59080.*

[9] Muhammad E.H. Chowdhury, Tawsifur Rahman, Amith Khandakar, Nabil Ibtehaz, Aftab Ullah Khan, Muhammad Salman Khan, Nasser Al-Emadi, Mamun Bin Ibne Reaz, Mohammad Tariqul Islam and Sawal Hamid Md. Al, R.P. (2021) . Tomato Leaf Diseases Detection Using Deep Learning Technique.

[10] Sood, S., & Singh, H. (2020). *An implementation and analysis of deep learning models for the detection of wheat rust disease. 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)*

[11] Oppenheim, Dor; Shani, Guy; Erlich, Orly; Tsror, Leah (2018). *Using Deep Learning for Image-Based Potato Tuber Disease Detection. Phytopathology, (), PHYTO-08-18-0288-R*

[12] UDAY PRATAP SINGH, SIDDHARTH SINGH CHOUHAN, (Student Member, IEEE), SUKIRTY JAIN, AND SANJEEV JAIN, R.P. (2019). Multilayer Convolutional Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease. IEEE Access 2019.

[13] Will Hamilton, Zhitao Ying, and Jure Leskovec. Inductiverepresentation learning on large graphs. In Advances in Neu-ral Information Processing Systems, pages 1024–1034, 2017.

[14] Jie Chen, Tengfei Ma, and Cao Xiao. FastGCN: fast learnin with graph convolutional networks via importance sampling .arXiv preprint arXiv: 1801.10247, 2018.

[15] Wei-Lin Chiang, Xuanqing Liu, Si Si, Yang Li, Samy Bengio, and Cho-Jui Hsieh. Cluster-gcn: An efficient algorithm for training deep and large graph convolutional networks. arXiv preprint arXiv:1905.07953, 2019.

[16] Jianfei Chen, Jun Zhu, and Le Song. Stochastic training of graph convolutional networks with variance reduction. arXiv preprint arXiv:1710.10568, 2017.

APPENDIX

Abbreviation

ResNet-50= Residential Energy Services Network-50(50 layers)

VGG-19= Visual Geometry Group-19(19 layers)

TL= Transfer Learning

Appendix: Reflections of Research

When we began our study effort, we knew essentially nothing about deep learning, artificial intelligence, or convolutional neural networks or graph convolutional networks. We were quite concerned about our research work. Because our supervisor, our study became a lot easier. He was a wonderful and helpful person with a big heart. He gave us directions and was quite helpful. Throughout our research, we learned about new algorithms, approaches, and a variety of other new things. In addition, we learned about Google Colab, the Python programming language and about some algorithms. We gradually gained a better understanding of Google Colab, the Python programming language, and a variety of other techniques. We have acquired bravery and been encouraged to accomplish more in the future after finishing this research effort.

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