PADDY DISEASE CLASSIFICATION USING DEEP 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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APPROVAL

This Project titled "**Paddy Disease Classification Using Deep Learning**", submitted by MD. Rasedul Islam ID: 173-15-10460 and Sharnali Paul Chaity ID:182-15-11479 and Sharmin Huq ID:182-15-11443 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 04/02/2023.

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We hereby declare that, this project has been done by us under the supervision of " **Ms. Most. Hasna Hena** "Assistant Professor, 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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ABSTRACT

Bangladesh is mostly an agricultural nation. A large portion of people is dependent on agriculture. But lack of proper knowledge of our farmers to classify the disease the quality and quantity of our paddy are declining.One of the biotic variables that limit paddy production the most is the illness.These illnesses can result in severe decreases in agricultural production and quality, which can result in substantial financial losses for farmers.A key aspect of protecting paddy crops is early disease diagnosis. Through our research, we are attempting to discover paddy infections. This study focuses on neural network methods for classifying rice diseases and image processing methods for enhancing image quality. This methodology includes image acquisition, preprocessing, segmentation, analysis, and classification of paddy diseases.It is very challenging to detect any disease by merely looking at the leaves.We suggested a procedure and Our system uses a state-of-the-art method called image processing. To do this, we use a transfer learning classification algorithm that is based on the CNN (Convolutional Neural Network) method. In This, we used VGG16, MobileNetV2, and EfficientNetB3 algorithms, Whereas MobileNetV2 attained 90% accuracy, VGC16 attained 92% and the EfficientNetB3 model performed better than the other two models, outperforming them with a maximum accuracy of 98%, indicating a successful result of this study.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

A summary of the studies that were carried out is given in this chapter. Any country's economy has always been centered on agriculture. Large fields of hectares are used to cultivate a variety of crops, including paddy, wheat, and maize. Although impediments like urbanization and city growth are there, there is greater demand than ever for agricultural products. Even when the farming area remains the same, technical elements are being incorporated into traditional farming to multiply the produce. Paddy Disease Classification Using Deep Learning is the name of our study. It includes background information, problems, goals, and the range of the study. Against the backdrop, the project's identification and related challenges are briefly described. The problem description outlines the issue identified and facilitates the execution of the chosen project. There are objectives mentioned for the project to accomplish. The study and user limits are included in the study's purview. The thesis's structure also gives a general idea of how its various chapters are organized.

1.2 Motivation

The time is right for creative transformation. Our lives have become much simpler and better thanks to technology. Agriculture plays a significant role in raising money worldwide, including in Bangladesh. Therefore, a favorable, practical climate is crucial for growth. closeness to agricultural buildings is necessary to ensure long-term human food security. The biodiversity of the tropics and subtropics is extremely rich in Bangladesh. Bangladesh is mostly an agricultural nation. 76% of the population resides in rural areas, and agriculture employs 47.5% of all workers. Additionally, the majority of them depend on paddy production. But our farmers' inability to recognize disease is the real issue. to go there In this instance, we considered figuring out how to address this drawback. We make an effort to use the most recent technology in this analysis. We should thus resolve this issue.

1.3 Rationale of the Study

Agriculture in Bangladesh provides sustenance for 163.65 million people on about 8.75 million hectares of land (Salam et al., 2014). Due to the rising population, more food will be needed in the future. Besides The most important and precious resource in the environment, as we all know, is the tree. But its current ratio does not meet the requirement for the whole growth of trees. Additionally, the growth is declining daily and the farmers lack the necessary skills to address it. The Existence of numerous uncommon plants already poses a concern. Modern humans are more drawn to technology than to the natural world. They can get oxygen thanks to technology. Additionally, chemicals are now used in place of food or vitamins. It is quite difficult for the growing number of people on the planet to develop an interest in trees and how to preserve them. So it is time to start thinking about using technology to research trees, plants, and leaves. Otherwise, we risk raising a generation that has little awareness of or respect for trees. But it's crucial for maintaining the environment's delicate equilibrium. Anyone can learn about paddy plants and their positive and negative consequences from the images through our study. We view it as a request that will at least spark some curiosity and assist farmers in getting the right plants.

1.4 Research Questions

1. How do we categorize and forecast?
2. Which algorithm produces the greatest results when the Deep learning algorithm is Used?
3. Which of these three algorithms will provide us with greater accuracy?
4. Should we employ a well-liked or fresh Deep learning approach?

1.5 Expected Output

The condition and its treatment are simple to recognize and Development of the agricultural industry. Our farmers have the ability to respond effectively when called upon.Our growers might create a paddy of high quality.It is advantageous for unemployed people to work in agriculture.

1.6 Project Management and Finance

In order to accomplish this, a project plan outlining the duties and deadlines for each model would need to be created. Each team member would also need access to resources like personnel and computing capacity. Additionally, we must make sure that our teams are collaborating well and that any problems or obstacles are quickly recognized and resolved. The project's overall cost would probably rise if numerous deep-learning models were used, from a financial perspective. Costs for gathering and processing data, as well as for training and testing each model, would be included in this.

1.7 Report Layout

This research study is divided into six chapters. Introduction, Background, Research Methodology, Working Procedure, Experimental Results and Discussion, Conclusion, and Future Research are the sections that make up this list.

Chapter 1: Introduction; Introduction, Motivation, the rationale of the study, Research Questions, Expected output, Project Management and Finance, and Report Layout.

Chapter 2: Background; Terminologies, Related Works, Comparative Analysis and Summary, Scope of the Problem, Challenges.

Chapter 2: This section has covered Related Works, Comparative Analysis and Summary, Scope of the Problem, and our Challenges

Chapter 3: Research Methodology; Introduction, Research subject, and instrumentation,Workflow, Data collection procedure, Statistical Analysis, proposed Methodology, and Implementation requirement.

Chapter 4: Experimental Results and Discussion; Experimental setup, Experimental result, and analysis, Discussion.

Chapter 5: Impact on Society, Environment and Sustainability; Impact on Society, Impact on Environment, Ethical Aspects, Sustainability Plan.

Chapter 6: Summary Conclusion Recommendation and Implication for Future Research; Summary of the Study, Conclusions, Implication for Further Study.

CHAPTER 2

Background Study

2.1 Terminologies

Different diseases can affect a variety of plant varieties. Similarly to that, this research describes a method for finding nine different illnesses in paddy plants. Algorithms determine accuracy by choosing images from the data. People will learn about paddy leaf and pulse diseases through this method. When this problem is adequately resolved, paddy production will rise. We'll try to understand more about these associated tasks and difficulties here in the chapter.

2.2 Related works

There are several articles on spotting crop diseases, but not many on paddy disease. Here are a few studies that are connected to the work on Paddy disease.

The author H. Q. Cap et al (2018) proposed the idea of using computers to identify plant diseases At 2.0 frames per second, our technique achieved 78% of the F1-measure detection performance.[1]

Prajapati et al. based on images of sick rice plants create a model framework for identifying and classifying diseases affecting rice crops. In order to address the problem of the automatic identification and grouping of diseases in the rice crop field, one of India's major food sources, this essay makes an effort to take the concepts of machine learning and image processing into consideration. Microbes, organisms, and infections are the root causes of all plant diseases. The provided framework was developed following a thorough examination of various techniques used in photo-handling jobs. The study looked at three diseases affecting rice plants (i.e., bacterial leaf blight, brown spot, and leaf smut). Three classifications have been created to group the various highlights (i.e., shading, shape, and surface). Support Vector Machine (SVM) has been employed for multiclass characterization, and on the training dataset and test dataset, respectively, 93.3% precision and 73.3% exactness have been achieved. The accuracy achieved after 5- and 10-fold cross-validation is, respectively, 83.80% and 88.57%.[2]

The author M. Jhuria et al (2013) proposed the artificial neuron network (ANN) algorithms to detect Rice Blast Disease. Three layers altogether are related to one another. Input neurons in

the first layer transmit data to hidden layers in the second layer, which then transmits proposed data to the third layer (output neurons).This method obtained the 90% of Blast detection performance. [3]
Anuradha badge had an idea “Crop disease detection using Machine learning: Indian Agriculture” How diseases are causing a decrease in yield, and how machine learning technology will help us find the disease and assist the farmers in taking the appropriate action. For the effective diagnosis of crop disease by taking images of the crop, they used Canny's edge detection method. For their study report, they choose the wheat crop.[4].

Wanjie Liang The proportions and origins of the afflicted areas were developed in order to examine their spread. Using deep neural networks and the Jaya optimization method for severe diarrhea,disease prevention, disease classification, prospective treatment, and planned fields monitoring Wheat can grow as a result of insects. Data from the Institute show that up to 37% of crops are lost to pests and illnesses each year by farmers.[5].

H. Andrianto proposed the concept of computer-based methods to detect plant diseases. This method demonstrates how creating a deep learning-based smartphone application for the detection of rice plant disease involves four steps: designing the architecture of the plant disease detection system, creating the application on a cloud server and the smartphone application, testing the smartphone application, and assessing the effectiveness of the plant disease detection system.[6]

2.3 Comparative Analysis and Summary

Nine different types of paddy plant diseases, including bacterial leaf blight, bacterial leaf streak, bacterial panicle blight, blast, brown spot, dead heart, Downy mildew, hipsa, and tungro, were the subject of this study. The CNN-based Transfer Learning classification technique is used in conjunction with these nine different categories. This implies that we can evaluate an image, establish the category it belongs to, and determine its accuracy.

2.4 Scope of the Problem

Using deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to accurately detect and categorize numerous diseases that damage paddy crops is known as paddy disease classification. This can involve evaluating symptoms, examining photos of harmed crops, and utilizing sensor system data to quickly diagnose and categorize illnesses. This issue's scope also encompasses the application of computer vision techniques to enhance the precision of disease detection and classification, as well as the incorporation of these deep learning models with precision agriculture systems to facilitate more effective and efficient crop management.

2.5 Challenges

- ➢ It took longer to find suitable software for resizing the photographs because of their big size.
- ➢ I was forced to switch platforms after discovering coding problems.
- ➢ Processing takes longer because there are many photos.
- ➢ There are few academic studies on diseases of paddy plants.
- ➢ We may now say that these tasks are challenging for us. Devices with high configuration levels are required for the system.

CHAPTER 3

Research Methodology

3.1 Introduction

Here are a few computer science algorithms for deep image processing. We decide to use CNN and Transfer Learning for 2D classification. Images are given layers. This method for categorizing photographs of diseased leaves could easily put an end to the condition. Use plant images and leaf samples to identify specific pre-harvest diseases including "Bacterial leaf blight, Bacterial leaf streak, Bacterial panicle blight, blast, Brown spot, Dead heart, Downy mildew, hipsa, tungro, " We looked at it to find out more about this paddy illness. There have previously been a number of similar studies on classification and image processing, and some wise observations have been made.

3.2 Research subject and measurement

The study in this area aids us in having a comprehensive understanding of our subject. After deployment and design, working with model applications, optimum data gathering, trustworthy data, and a training model. We operate on the Windows operating system. Python was utilized to complete the task. Among the several library packages and programming languages used are CSV, Keras, Numpy, OpenCV, Sklearn, and TensorFlow. Virtual environments and a Jupiter Notebook were employed.As a programming language we pick python trusted for testing and deep learning of algorithms-heavy applications. We would have encountered numerous issues if not for the virtual environment. relating to installing libraries and packages. We invested much in Google Colab on my PC in a virtual environment to overcome this issue.

3.3 Workflow

Firstly, we collect data. The image is resized after some good and sharp images are selected from our collected data. We split the image categories into a test set and a training set, finally having for training 80% of the data and using 20% of the data for testing to get the accuracy based on the algorithm. Figure 3.1 shows the workflow diagram.

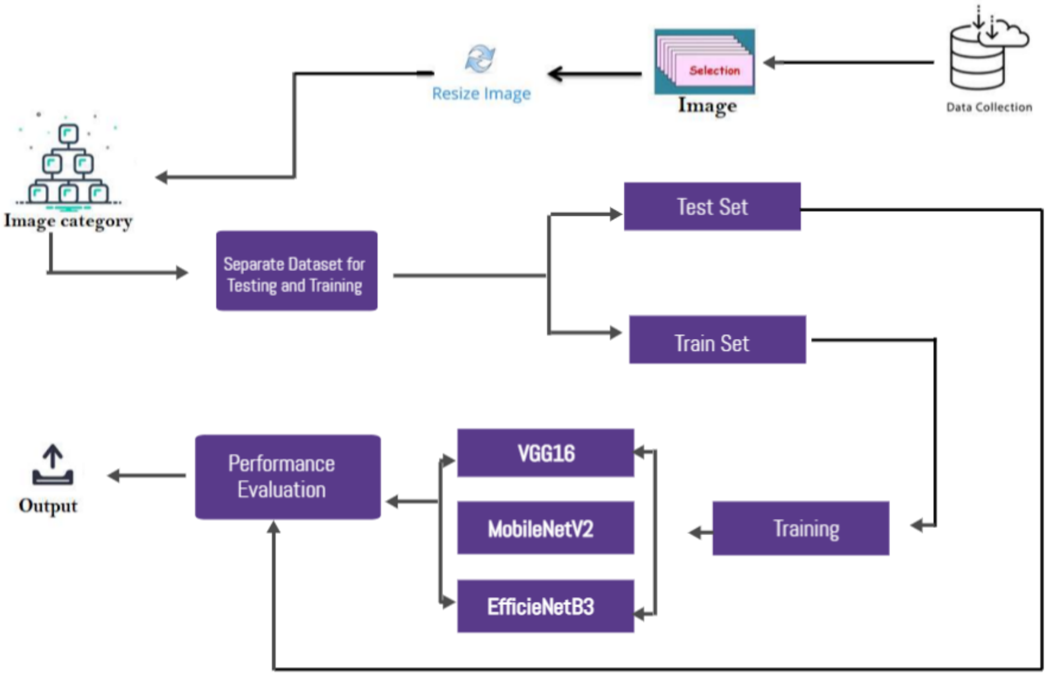

Figure 3.1: Workflow diagram

3.4 Data collection procedure

Sets of data are crucial to deep learning. There is no time to begin creating a deep-learning model. It is necessary to collect or develop a dataset of real-world scenarios or events that can be categorized. Verify the model and successfully train it. The investigation produced a fresh dataset for the suggested network training.On Kaggle, dataset[A1] was gathered from the paddy's branches and leaves. Grams Each JPG-formatted image has a distinct resolution. Pre-harvest diseases such as bacterial leaf blight, bacterial leaf streak, bacterial panicle blight, blast, brown spot, dead heart, Downy mildew, hipsa, tungro, and normal are depicted in a train set total of 10407 pictures in the data collection. Of the 13,876 photos, 75% were used for training and 25% for testing.

Bacterial leaf blight illness,which includes the Bacterial leaf blight class, is depicted in Figure 3.2.

Figure 3.2: Bacterial leaf blight

Bacterial leaf streak illness,which includes the Bacterial leaf streak class, is depicted in Figure 3.3.

Figure 3.3 : Bacterial leaf streak

Bacterial panicle blight illness,which includes the Bacterial panicle blight class, is depicted in Figure 3.4.

Figure 3.4 :Bacterial panicle blight

Blast illness,which includes the Blast class, is depicted in Figure 3.5.

Figure 3.5 : Blast

Brown spot illness,which includes the Brown spot class, is depicted in Figure 3.6.

Figure 3.6: Brown spot

Dead Heart illness,which includes the Dead Heart class, is depicted in Figure 3.7.

Figure 3.7 : Dead Heart

Downy mildew illness,which includes the Downy mildew class, is depicted in Figure 3.8.

Figure 3.8: Downy mildew

Hispa illness,which includes the Hispa class, is depicted in Figure 3.9.

Figure 3.9 : Hispa

Tungro illness,which includes the Tungro class, is depicted in Figure 3.10.

Figure 3.10: Tungro

Normal or Healthy paddy,which includes the Normal class, is depicted in Figure 3.11.

Figure 3.11: Normal

3.5 Statistical Analysis

In this study, we propose to detect paddy illnesses such as Bacterial leaf blight, Bacterial leaf streak, blast, Brown spot, Dead heart, Downy mildew, hipsa,tungro, and a healthy class using 10407 image data for training. In this study, project.jpg picture formats are permitted. Nine excellent classes are listed below:

1. Bacterial leaf blight

Causative agent: Bacteria, Xanthomonas oryzae PV. Oryza.

Symptoms:

yellowing of leaves or wilting of seedlings at the seedling stage (called kresek). Kresek damage to seedlings can occasionally be mistaken for early rice stem borer damage. When leaves are pressed, Kresek should produce a yellowish bacterial ooze that can be used to identify it from stem borer damage. Rice plants with kresek cannot be plucked from the ground as easily as ones infested with stem borer.On mature plants, lesions generally show up as orange stripes on the leaf blades or leaf tips. The edge of the lesions is wavelike, and they advance to the leaf base.

Condition that makes the sickness more likely :

1. It can happen in lowland areas that are both rainfed and irrigated.
2. Favors 25 to 34 °C temps.
3. When there are strong gusts and persistent, heavy rains, it frequently happens.
4. High humidity.
5. excessive nitrogen fertilizer application.

Disease Management:

1. Make sure the fields are well-drained.
2. Stop the water supply as soon as the disease is discovered, and allow the area to dry.
3. Try to out-flow water through drainage ditches when complete water removal is not practicable.
4. As little as feasible should be done to redirect water from contaminated farms through healthy fields.
5. Once the disease has been identified, potassium fertilizer application may be used to control its further spread.

2 . Bacterial leaf streak

Causative agent: Xanthomonas oryzae pv. Oryzicola

Symptoms:

At first, there were a few tiny, dark-green, wet streaks on the interveins between the tillering and booting stages.The longitudinal progression of the streaks is constrained by the veins, and they quickly turn yellow or orange brown.Bacterial exudates were visible as minute yellow or amber-colored droplets along the entire length of the streaks.Large areas of these streaks could form and cover the entire leaf surface.When the condition is severe, lesions change from brown to greyish white before drying.Infected florets and seeds exhibit brown or black discolouration, ovary, stamen, and endosperm death, as well as browning of the glumes.

Condition that make the sickness more likely :

1. Bacteria on leaves, in water, or those surviving in waste materials left over from harvest.
2. High humidity and a warm temperature.
3. From maximal tillering through panicle initiation, the early planting stage.

Disease Management:

1. By applying nutrients correctly, spacing plants appropriately, choosing resistant types, and treating seeds in hot water, the disease can be managed.
2. Field sanitation is crucial to practice.
3. It is possible to reduce the initial inoculum at the start of the season by destroying volunteer plants, straws, and rats left over after harvest.
4. This disease can also be controlled by installing an effective drainage system, especially in seedbeds.
5. The best way to prevent bacterial leaf streak is to plant resistant types (IR 20, TKM 6).
6. Grow nurseries ideally in solitary upland environments.
7. When transplanting seedlings, avoid trimming them.
8. Spray 20% of lemon grass, mint, or fresh cowdung water extract.
9. spraying a mixture of 300g of copper oxychloride and 1.25 kg of streptomycin sulphate and tetracycline per hectare.

3 . Bacterial panicle blight

Causative agent : Bacterium Burkholderia glumae.

Symptoms:

On plantlets, the sheath of the flag leaves, and panicles, symptoms can be noticed. The infected spikelet exhibits a straw-colored pigmentation, as well as grain deterioration, rotting, and panicle blanking. When conditions are perfect, germs grow swiftly. Three days after the panicles are inoculated, the symptoms begin to show, and the number of panicles afflicted gradually increases.

Disease Management :

1. Applying the right amount of the active component while taking the product's quantity and quality into consideration.
2. Applying the product at the right time is important because it works to prevent symptoms from appearing.
3. Introducing an integrated management program that consists of the following to manage B. glumae:
4. the usage of only the best-certified seeds.
5. Chemical seed treatment combined with preventative foliar spraying
6. fertilizing and irrigation done correctly.
7. the adoption of partially resistant cultivars, which lowers the rate at which diseases emerge.
8. getting rid of harvest waste
9. crop revolving.
10. Short cycle varieties and early crop sowing.
11. Choosing the right dates for planting.

It can be used to treat plants at the panicle emergence stage or applied by spraying or soaking seeds.

When it comes to treating soil, it has been observed that using 10% dusting of the chemical compound methasulfocarb [S-(4-methylsulfonyloxyphenyl) N-methyl] thiocarbamate is effective when treating low amounts of B. lumae inoculum.

4 . Rice blast

Causative agent: Fungus

Symptoms:

Common symptoms include leaf spots that resemble spindles and have pointed ends, ashy centers, and brown or reddish/yellowish-brown edges. Full-grown lesions typically measure 1.0–1.5 cm in length and 0.3–0.5 cm in width.Nodes decay and turn black when they are diseased. The panicle falls off when the panicle base becomes infected because it develops a rotten neck or neck rot. When the infection is bad enough, secondary branches and grains are also affected, which leads to partially filled grains, or "whiteheads," on the grains. The crop life stage, the cultivar's level of susceptibility, and environmental conditions all affect characteristics differently.

Conditions that make the sickness more likely:

1. Low nighttime temperature (17-20OC).
2. extreme humidity
3. fertilizer with too much nitrogen being used.
4. gloomy and foggy weather conditions.
5. high plant population densities in the field.
6. vulnerable species.

Disease Management:

1. use of resistant species (Bg 403, Bg 406, Bg 366, Bg 359, Bw 361, Bg 250)
2. Use only verified disease-free seed paddy.
3. 250 kg of burnt paddy husk per acre is added to the soil during the land preparation process.
4. Avoid including straw that has been exposed to illness.

5 Brown Spot

Causative agent: Fungus Cochliobolus miyabeanus (Bipolaris oryzae).

Symptoms:

On the coleoptiles, the fungus develops brown, oblong to circular patches that can cause seedling blight. Seedling blight may cause weak plants and sparse or insufficient stands. On immature leaves compared to higher leaves, the dots are smaller. The spots can range in size and shape from tiny (black, brown to reddish brown) spots to huge oval or circular marks. The hulls and sheaths of the leaves both have markings that resemble the spots on the leaves. On infected glumes, a pervasive black staining could be visible. Attacking the young florets may impede grain development or result in the formation of light-weight.

Condition that makes the sickness more likely :

1. Temps in the surrounding area range from 16 to 36 OC.
2. (86-100%) High relative humidity
3. insufficient levels of the necessary nutrients in the soil or problematic soils.
4. Drought

Disease Management:

1. The quality of the soil will improve with the use of organic fertilizer.
2. Use only verified disease-free seed paddy.
3. During the land preparation procedure, 250 kg of burnt paddy husk are put to the soil each acre.
4. Avoid including straw that has been exposed to illness.
5. Treatment involves submerging a seed paddy for 10–12 minutes in hot water (53–54 OC).
6. application of a seed-protecting fungicide to the seeds.
7. crop revolving.
8. proper leveling of the terrain.

6 Dead heart

Causative agent: Rice Stalk Borer, Chilo plejedellus (Zink).

Symptoms:

1. brown egg mass is present close to the leaf tip.
2. The core stalk, sometimes known as the "dead heart," of rice seedlings and tillers is dried by caterpillar bores.
3. Whole panicle of a mature plant turns dried "white ear."
4. Plants were simple to pull by hand.

Disease Management

1. Trichogramma japonicum, an egg parasitoid, is released at ATL in order to eradicate the rice yellow stem borer.

2. Controlling stem borer requires spraying neem seed kernel extract.
3. Before transplanting, trim the seedling tips to remove egg masses, and then gather and kill the egg masses in the field.

7 Downy mildew

Causative agent: Sclerophthora macrospora.

Symptoms:

1. On the upper leaf surface, downy mildew infection first appears as angular yellow patches.
2. After that, they develop dazzling yellow dots.
3. Eventually, these dots develop brown interiors with yellow edges.
4. This sick leaf has fine, grayish fungal growth on the underside. Young shoots, fruits, and seeds that have been infected have a white coating of fungus spores.
5. On the undersides of the leaves, downy fungal growths are frequently visible in the early morning.

Disease Management:

1. Only seeds free of illness should be chosen and sown. Buy seeds that are resistant to downy mildew if you can.
2. Only transplant seedlings in good health.
3. Make sure your soil is properly prepared for the land to ensure good drainage.
4. To lower canopy density and reduce humidity, leave enough space between the rows and the hills for plants. New growth pruning is also beneficial for optimal plant aeration.
5. Cut down infected shoots and remove infected plants. However, to stop the disease from spreading further, carry out these hygienic procedures while the plants are not damp. Burn or bury the gathered sick components to properly dispose of them.
6. Avoid watering from above. It prolongs the period of leaf wetness and encourages the disease's further progression.
7. Plow under all the plant detritus after harvest.

8 Hipsa

Symptoms:

The grub mining will be evidently visible on the leaves. The top of the leaf blade was scraped off, exposing just the bottom epidermis, which appeared as white streaks parallel to the midrib.even translucent white patches that run parallel to the leaf veins are the result of larvae tunneling into leaf tissue. Leaf damage causes it to wither. When extensively infested, rice fields resemble charred terrain. The grub eats the green tissue found between the veins by tunneling into the leaf blade. Adults eat the green tissue as well; they scrape the green substance from the fragile leaves. In most cases, young plants are when they are damaged.

Disease Management:

1. Don't over-fertilize the lawn.
2. Greater leaf densities from close plant spacing allow for increased hispa tolerability.
3. Blotch mines should be removed from leaf tips.
4. Using hand nets, beetles can be manually collected and killed.
5. The shoot tips can be clipped to stop the bugs from laying eggs.
6. By cutting and burying shoots in the mud, grub populations can be reduced by 75% to 92%.
7. The adults are eaten by the reduviid bug.
8. Quinalphos or methyl parathion 0.05% spraying

9 Tungro

Causative agent:

Causal virus:

RNA virus -

rice tungro sphericalvirus (RTSV)

DNA virus -

rice tungro bacilliformvirus (RTBV)

Symptoms:

Both RTBV and RTSV-infected rice plants exhibit characteristic symptoms of a tungro, including stunting and yellowing or orange-yellowing of the paddy leaves.Infected paddy plants have delayed and frequently incomplete panicle development, and some panicles shorten and produce sterile or partially packed grains.RTBV alone causes symptoms in plants that are comparable to but less severe than those caused by both RTBV and RTSV.A plant with RTSV infection alone may not show any symptoms or only show very moderate stunting.

Disease Management:

The following are examples of cultural practices (cultural control):

1. Planting should be done when there are few virulent GLH populations and few tungro cases.
2. Planting in synchrony: Planting rice crops at around the same time to stop the spread of tungro
3. removing the source of the inoculum by plow under infected stubbles.
4. Direct planting; the prevalence of tungro is frequently lower in rice that is direct-seeded; dense plant populations lessen the likelihood that GLH will detect and eat infected plants.

3.6 Proposed Methodology

We used a transfer learning algorithm built on a convolutional neural network (CNN) in our methodology. Three transfer learning techniques—VGG-16, MobileNetV2, and EfficientNetB3 were used. Below is a thorough description of the Convolutional Neural Network (CNN) theory that is pertinent to transfer learning.

3.6.1 Convolutional Neural Networks (CNN):

Convolutional Neural Network, or CNN for short, is a class of artificial neural network used in computer vision and image identification. Convolutional and pooling layers of the network are intended to process data having a grid-like architecture, such as an image. While the pooling layer shrinks the spatial scale of the representation to minimize computational cost and control overfitting, the convolutional layer adds filters to local patches of the input. Modern performance on a range of visual recognition tasks has been attained using CNNs.

3.6.2 VGG-16:

The Visual Geometry Group at the University of Oxford created the Convolutional Neural Network (CNN) architecture known as VGG-16. In the 2014 study "Very Deep Convolutional Networks for Large-Scale Image Recognition," it was first introduced.The architecture of the VGG-16, which consists of 16 layers, comprising 13 convolutional layers and 3 fully connected layers, has this name. Because it just uses 3x3 convolutional filters and has a deep architecture with several layers to boost the network's capacity, the VGG-16's simplicity is its defining feature. VGG-16 has received a lot of attention as a feature extractor for a range of computer vision tasks and has produced cutting-edge outcomes on numerous benchmark datasets.Figure 3.12 describe the architecture diagram of VGG-16.

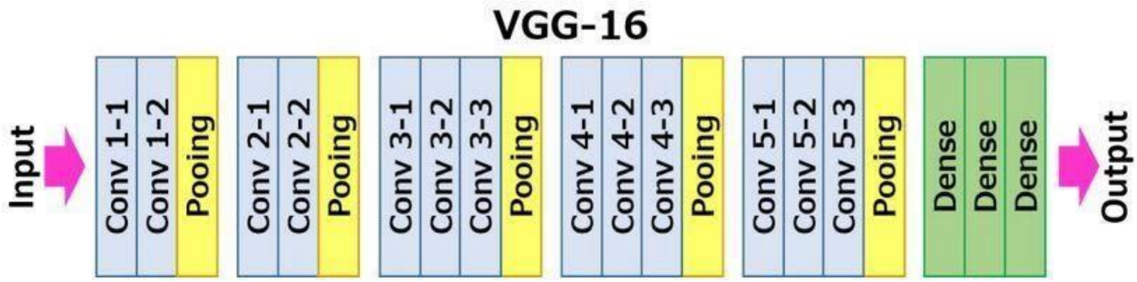

Figure 3.12: Architecture Diagram of VGG-16.

3.6.3 MobileNetV2:

A lightweight Convolutional Neural Network (CNN) architecture called MobileNetV2 was created for effective mobile and embedded device deployment. The accuracy and computational efficiency of MobileNetV2 are balanced, making it an excellent choice for deployment on limited-resource devices like cellphones and Raspberry Pis. This is accomplished by combining inverted residual blocks, which boost the network's capacity for representation, with depthwise separable convolutions, which minimize the amount of parameters and computation. Compared to other cutting-edge models, MobileNetV2 has demonstrated competitive accuracy on a range of visual identification tasks. It is also substantially more efficient.Figure 3.13 describe the architecture diagram of MobileNetV2.

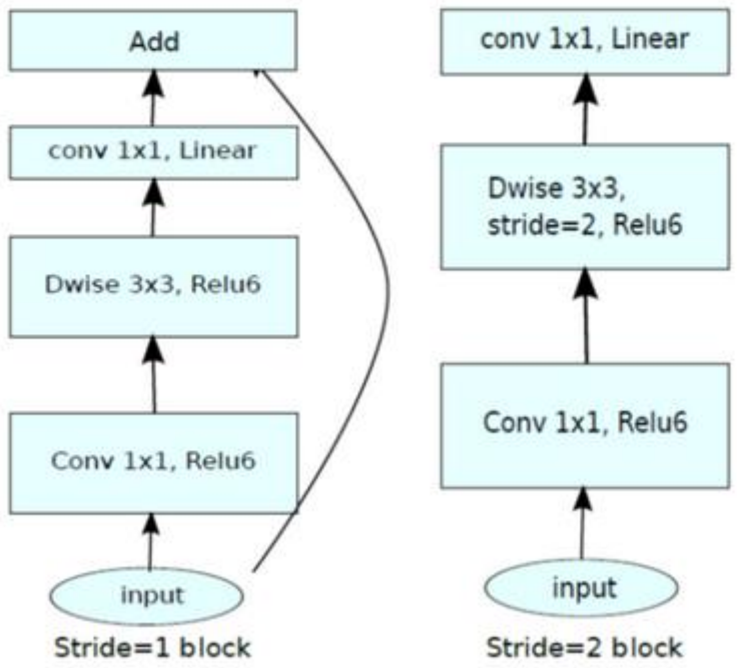

Figure 3.13: Architecture Diagram of MobileNetV2**.**

3.6.4 EfficientNetB3:

Convolutional neural network (CNN) model EfficientNet-B3 was created by Google Research. The model is a member of the EfficientNet family of models, which aim to provide computationally efficient and state-of-the-art performance on image classification tasks. The biggest member of the EfficientNet family is EfficientNet-B3, which is the model's third iteration. The ImageNet dataset, a sizable dataset of images classified with 1000 different classes, is used to train EfficientNet-B3. The model can accurately identify a wide variety of items and scenes in photos. To enhance performance, the model employs a compound scaling technique that increases the model's resolution, depth, and width. Object identification, image segmentation, and image synthesis are just a few of the computer vision tasks that EfficientNet-B3 can be utilized for. The model is suited for practical applications including self-driving automobiles, drone image identification, and picture-based search engines due to its high accuracy and processing economy. Figure 3.14 describe the Architecture Diagram of EfficientNetB3.

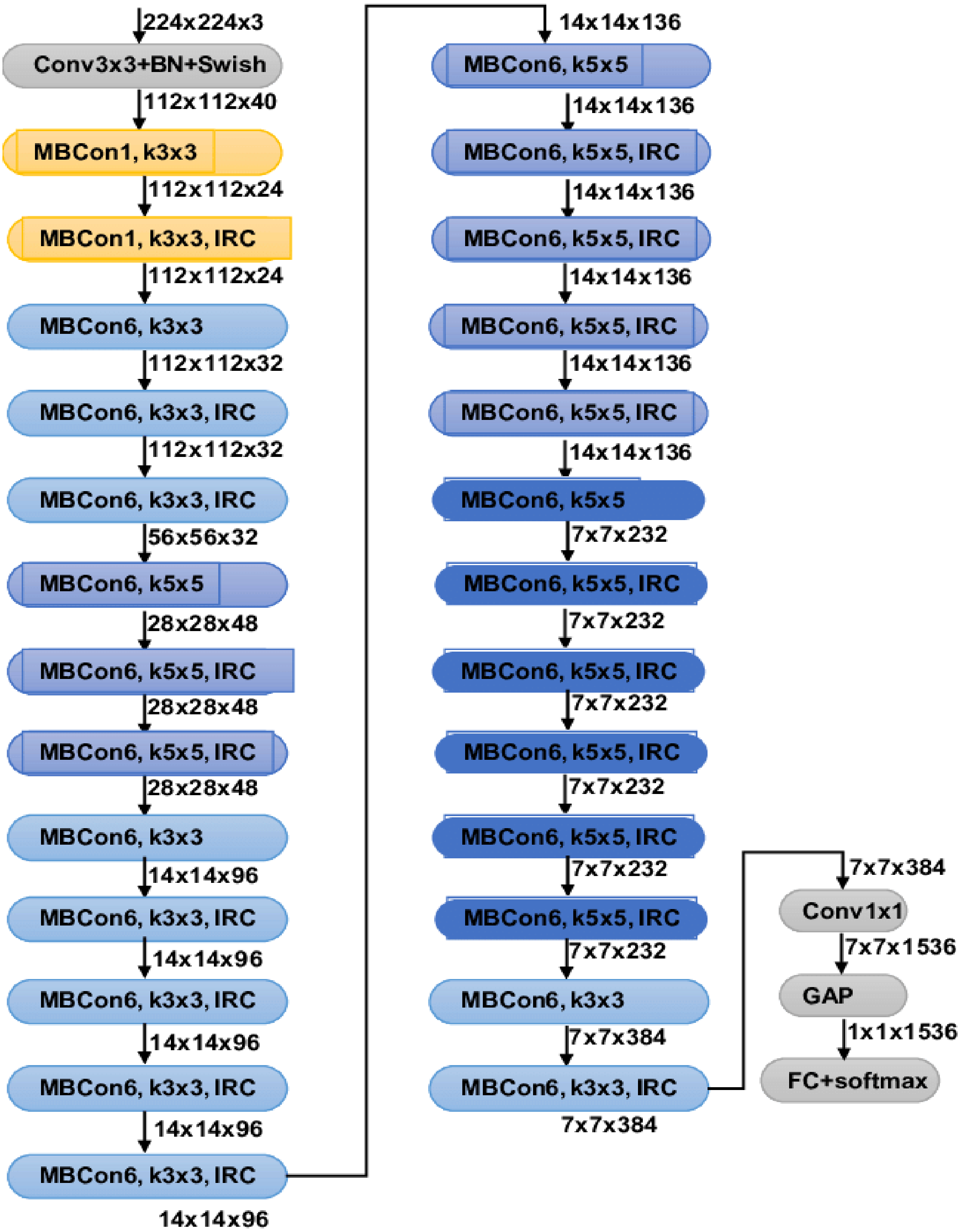

Figure 3.14: Architecture Diagram of EfficientNetB3.

3.7 Implementation Requirements:

We used test data to gauge the models' performance after training. Below is a list of the metrics that were calculated for performance assessment. Using these factors, we determined which model was able to forecast the result the most accurately. Using Eqs. (1–4) and the confusion matrix the model provides, numerous percentage performance indicators have been created.

Accuracy =(True Positive Number + True Negative) / Total Number of Image * 100 % (1)

Precision = True positive / (True positive + False Positive) * 100% (2)

Recall = True Positives / (True Positives + False Negatives) (3)

F1 Score = 2 * ((Precision * Recall) / (Precision * Recall)) * 100% (4)

CHAPTER 4

Experimental Result and Discussion

4.1 Experimental Setup

Our experimental setup has amassed a vast body of knowledge regarding algorithms in several languages. We start by 13876 gathering pictures from Paddy . If we like, we can utilize additional data since the more data we use, the more precise the outcomes of our experiment will be. We divided the data we obtained for this research into two sets, a training set, and a test set, with the goal of classifying photos more accurately. We have addressed the idea of many illnesses affecting the paddy plant after reading numerous study publications. We classified paddy tree diseases into 10 classes. We gathered 1738 images for the blast, 343 photos for the bacterial leaf blight disease, 260 images for the bacterial leaf streak, 313 images for the bacterial panicle blight, 965 images for the brown spot, 1442 images for the dead heart, 620 images for the downy mildew, 1594 images for the hipsa, 1088 images for the tungro, and 1764 images for the fresh, healthy normal plant for training purpose. 3469 photos were chosen for testing and 10407 were chosen for training. The data is set up in this manner.

4.2 Experimental Results & Analysis

Table 4.1 shows the accuracy of VGG16,MobileNewV2 and EfficientNetB3.Where we got the best accuracy for EfficientNetB3 with 98%.

Table 4.1: Accuracy Table

Model Name	Epoch	Accuracy
VGG 16	50	92 %
MobileNetV2	30	90 %
EfficientNetB3	20	98%

4.2.1 Accuracy graph

We have three algorithms in use. Furthermore, the highest accuracy rate has originated from EfficientNetB3.Figure 4.1 shows the accuracy graph of EfficientNetB3.

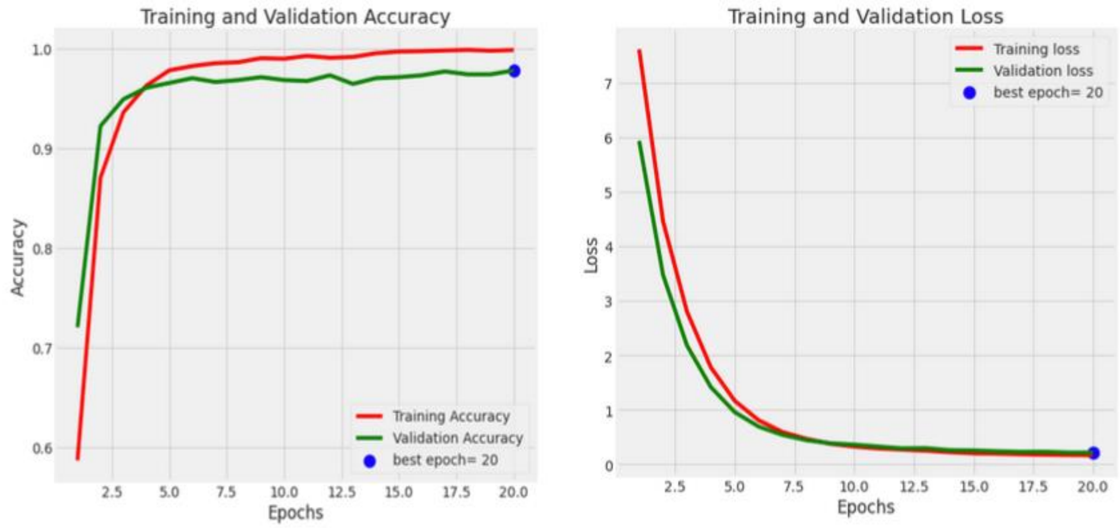

Figure 4.1: EfficientNetB3

4.2.2 Confusion Matrix

Here Figure 4.2 shows the Confusion Matrices of the EfficientNetB3 algorithm.

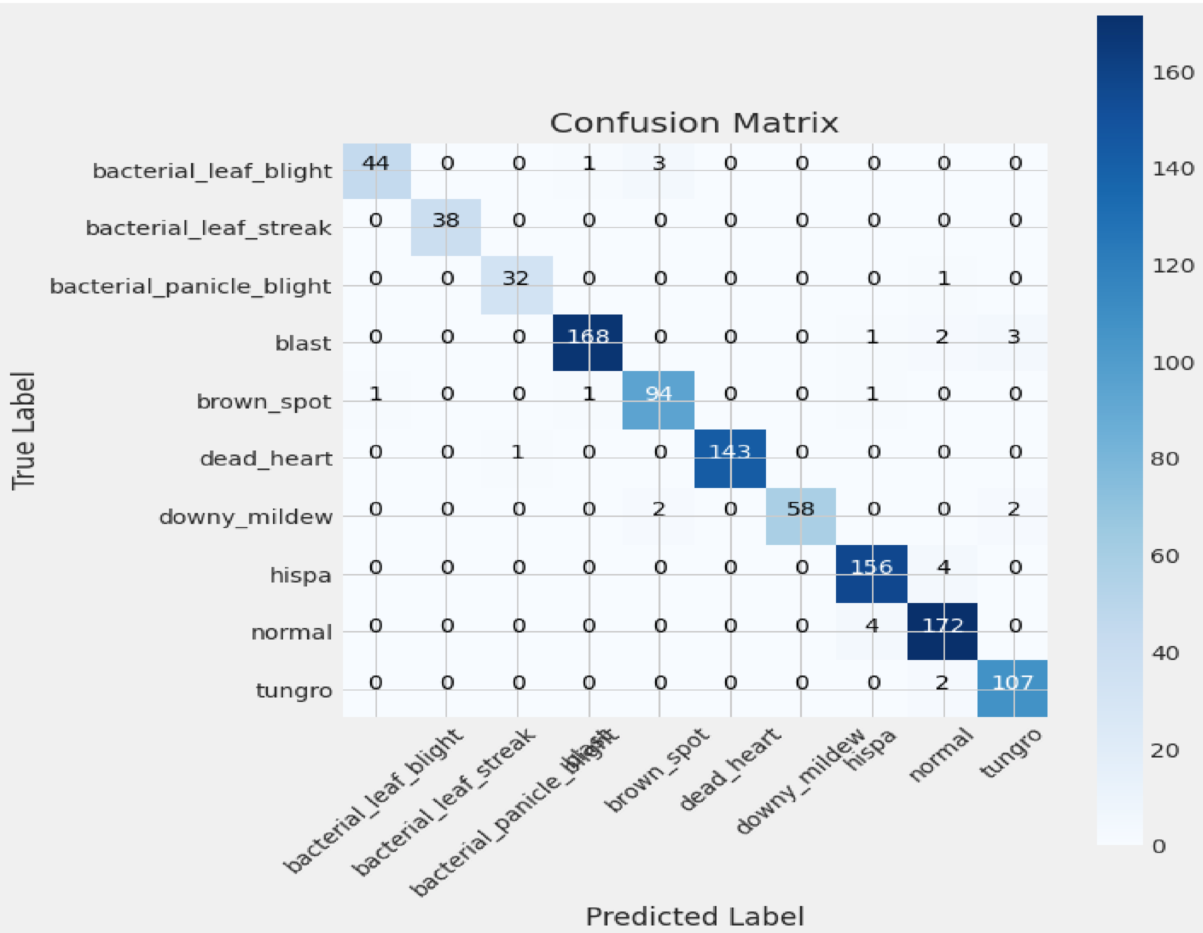

Figure 4.2: Confusion Matrices of the EfficientNetB3

4.2.3 Performance Matrices

Here Table 4.2 shows the Performance Matrices of the EfficientNetB3 algorithm Where we got the best precision score for Bacterial leaf streak, Dead heart, and Downy mildew. And best recall score for the Bacterial leaf streak, and we got the better f1-score for the Bacterial leaf streak and Dead heart.

Table 4.2: Performance Matrices of EfficientNetB3 algorithm.

Class	precision	recall	f1-score	support
Bacterial leaf blight	98	92	95	48
Bacterial leaf streak	100	100	100	38
Bacterial panicle blight	97	97	97	33
Blast	99	97	98	174
Brown spot	95	97	96	97
Dead heart	100	99	100	144
Downy mildew	100	94	97	62
Hispa	96	97	97	160
Normal	95	98	96	176
Tungro	96	98	97	109

4.4 Discussion

For the paddy plant, identification is a crucial stage. One must endure numerous losses if the ailment is not detected in a timely manner. Farmers will be able to detect this disease early and minimize damage thanks to the development of contemporary techniques and technology. As a result, in order to address this issue, we looked for a diagnosis approach using the VGG16, MobileNetV2, and EfficientNetB3 algorithms to identify paddy diseases. We used our extensive understanding of CNN to confirm the accuracy of the research's findings. We have demonstrated the excellent results of EfficientNetB3 using graphical and numerical categorization. These values perfectly captured the goal of our study, that will be extremely helpful for other studies.

CHAPTER 5

SUMMARY,CONCLUSION,RECOMMENDATION, IMPLICATION FOR FUTURE RESEARCH

5.1 Summary of the Study

The major goal of this research is to use deep learning to identify paddy diseases.The CNN algorithm was utilized. There are many different CNN models available.we found that in our dataset, EfficientNetB3, MobileNetV2, and VGG16 performed well with a high accuracy. EfficientNetB3 is performing wonderfully in comparison to MobileNetV2 at 90% and VGG16 at 92% with an accuracy of 98%.

5.2 Conclusion

We have done all possible to get the best outcomes. These initiatives show a lot of promise for assisting Bangladesh's agriculture sector. most of Bangladesh's farmers lack knowledge and are unaware of the best methods for diagnosing and treating diseases. Farmers are hurt by the crops' daily, gradual deterioration. As a result of this study, Bangladeshi farmers' situation could significantly change. There is a lot of room for further development of this prototype.

5.3 Recommendation

Deep learning is a potent method for classifying images and has been extensively utilized in illness detection and medical imaging.Creating a sizable dataset of photos of both healthy and ill paddy plants is the first stage. Ensure that the photographs are clear and include the appropriate disease designation.The photos need to be processed before being input into the deep learning model. To expand the dataset size and decrease overfitting, this may involve procedures like cropping, resizing, normalization, and augmentation.Select a deep learning model that is appropriate for the job. Convolutional Neural Networks (CNNs) are frequently employed for image categorization and are capable of delivering cutting-edge results. Starting from a pre-trained model like ResNet or Inception, you can refine it using the paddy disease dataset.Utilize the annotated picture dataset to train the deep learning model. To track the model's progress during training, divide the data into training and validation sets. To evaluate the generalization performance of the model, use methods like cross-validation.The model can be deployed for use in the field after being trained and assessed. For simple access, you can implement the model on a mobile device or online application.

Always verify the outcomes using actual data, and keep an eye on the model's performance to make sure it's still accurate and useful.

5.4 Implication for Further Study

The movement of a farmer's crops to other growing places can be stopped. Therefore, when creating this system, a few presumptions should be taken into account. For the image to be clear and simple for the system to extract the function, the camera needs to have enough pixels. In order to improve the current study, additional research should be conducted in light of the aforementioned inadequacies. The technology that can be used to new datasets, or it can be used to analyze this dataset using various deep learning techniques, and we have some proposals for further study to support this system in the agriculture industry. This technology ought to be used in the creation of mobile applications as well. to enable rice farmers to identify the different rice illnesses with only a cell phone

CHAPTER 6
IMPACTS OF OUR PROJECT

6.1 Impact on society

Because it interferes with the development of the paddy plant and the production of the crop, paddy disease is a major problem for society. More than half of the world's population relies on paddy as a staple meal, and paddy illnesses can cause considerable crop losses, resulting in food insecurity and economic hardship for farmers. It may also result in higher food prices in some areas, which would reduce consumer purchasing power, especially among lower-income populations. Further harming the economies of nations that depend on exporting rice is the possibility that disease outbreaks will reduce export opportunities. It is a major factor in the lack of food accessible since it severely reduces paddy yields, for humans. This is a major factor in why people starve and die from hunger.

6.2 Impact on environment

To live a healthy life, we as humans require a healthy environment. We require quality meals in order to live wealthy lives. Our research will aid in the environment's ability to produce more food since it will identify diseased leaves at an early stage, which increases the likelihood that the plant will survive. A favorable effect on the environment can result from the early discovery of paddy illnesses. Early disease detection allows farmers to take more precise, less hazardous management techniques, which reduces the need for extensive chemical use. This can lessen the amount of harmful chemicals released into the environment and reduce the possibility of the emergence of disease strains that are resistant to pesticides. Early detection can also lessen the scope and severity of disease outbreaks, preserving important wildlife habitats and preventing the eradication of extensive rice fields. Additionally, minimizing paddy disease effects through early diagnosis can aid in maintaining the general health of ecosystems and safeguarding the environment for future generations. Additionally, by saving the plant, additional food will naturally grow. The fewer infected areas there are, the fewer have more serious issues. Early identification of leaf disease allows us to increase food production.

6.3 Ethical aspects

The majority of wealthy nations are able to produce more food because their technologies are highly advanced and provide extremely high levels of precision when identifying plant leaf disease. We were compelled to act because, in our nation, farmers are losing significant crop yields as a result of inadequate technology. We took this action in order to support farmers and assist them in producing more crops. so that people in our nation have access to enough food and do not suffer from starvation.The responsibility for disease control is shifted from governments to individual farmers as a result of the early discovery of paddy diseases. This may impose an excessive burden on farmers and cast doubt on the government's ability to provide food security and preserve the environment.

6.4 Sustainability Plan

As we produced this work with the farmers and their hardships in mind, it will be one of the most distinctive and practical pieces. They will benefit greatly from it and will work many miracles for them. In order to complete this task, we used photographs as the input data. It may be able to tell apart between leaf Bacterial leaf blight, Bacterial leaf streak, Bacterial panicle blight, blast, Brown spot, Dead heart, Downy mildew hipsa and tungro. It will provide extremely high accuracy, which will benefit us much.

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Appendix

A1. Dataset of paddy Disease

RS2

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