Smart Detection and Classification of Fungal Disease in Rice Plants Using Image Processing Techniques

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A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
Bachelor of Science in Computer Science

Department of Computer Science and Engineering
Brac University
May 2024

Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Abstract

One of the most crucial staple crops, rice (Oryza Sativa), feeds a significant percentage of the world's population. However, fungal infections, which may significantly reduce yields and affect global food security, represent an extreme risk to rice's productivity and quality. We created a custom dataset of 991 images capturing both healthy and False smut affected rice plants. Several state-of-art deep learning models including ResNet50V2, AlexNet, VGG19, VGG16, InceptionV3, and CNN architecture were applied to classify the disease. The models were trained, validated and tested on our dataset, and the performance was analyzed based on metrics such as accuracy, precision, recall, and F1-score. Among all the models, Inception V3 achieved the highest result with an accuracy of 99.49%. The result of the research will further contribute to developing a web application for identifying and diagnosing fungal blasts in rice plants to ensure better rice cultivation, enabling early intervention and sustainable crop management practices.

Keywords: Fungal infections; False Smut; Disease detection; Machine learning; Custom dataset; Binary Classification; Deep Learning; Automated Disease Detection; User-Sustainable Agriculture;

Acknowledgement

All praises and thanks to the Almighty Allah for guiding us and letting us finish the project on time successfully. Secondly, we would like to thank our supervisor Md Sabbir Ahmed and our co-supervisor Dibyo Fabian Dofadar for guiding us and keeping us motivated during the tough times. Finally, we would like to thank Amal Karishna Paul, Sub Assistant of Bangladesh Krishi Somprosaron, Sharsha, Jessore who helped us to collect an authentic dataset required for this project.

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Chapter 1

Introduction

1.1 Background Information

Rice is the most common and dependable commodity that serves as the main source of nutrition for a sizeable portion of the global population. However, the risk of fungal disease to rice fields is a recurring issue that might jeopardize production and global food security. In addition to reducing yields, fungal infections in rice plants may affect the quality of the produced grains. To retain the dependability and sustainability of rice cultivating systems, it is crucial to address the problems caused by fungal diseases. The research focuses on the complex world of fungal infected disease in rice plants named Rice False Smut that cause loss in the productivity of rice through ensuring a detailed investigation of its several strains, means of transmission and using systematic control techniques. The research utilizes images processing techniques in advanced levels and it will be used to create a smartphone application in order to achieve precise and fast recognition and classification of the rice plant False Smut. Convolutional Neural network and deep learning architectures will be used for achieving a higher accuracy with accurate and effective classification. Early detection and accurate classification of fungal diseases in rice plants are crucial for farmers to take necessary precautions early to prevent the disease. This study will start with an introduction of fungal diseases. The ability of farmers to control the disease at the early stage of infection by interrupting the infection process and to some extent reducing the negative effects of the disease depends on the timely identification of the disease in the rice plants. The goal of this research is to assist farmers in identifying issues early on and make informed decisions by bringing together innovative computer vision technologies and the versatility of smartphone apps. This work closes the gap between technology and agriculture by utilizing the visual cues displayed by sick plants, allowing farmers and researchers to take effective action against fungal disease in rice plants. The three main supporting concepts of this study include the following. In the first place, a comprehensive description of different types of rice plant fungus infections will be given with a focus on their characteristics and possible outcomes. Image processing techniques for the context of rice plant disease detection then becomes the next topic of investigation. An application for the web will be created for actualization of the knowledge acquired. This application will help to diagnose the fungal blast based on visual images of rice plants using machine learning and image processing technologies and detect it more quickly and accurately.

Overall, the proposed study bridges the gap between the theoretical and applied aspects. It designs an app that allows farmers to distinguish and assess the severity of the fungal infection in their rice paddies on their own. The software seeks to revolutionize disease control practices by offering an accessible tool for plant picture-taking as well as analysis. This project aims to herald a new era of informed decision-making, protecting rice production and guaranteeing food security on a global scale by democratizing access to crucial information.

1.2 Problem Statement

In Bangladesh's agriculture sector, the role of human intelligence for crop production and management specifically in complex areas is crucial. Plant inspection from the beginning is important for ensuring better crop production in our country which is highly dependent on agriculture. Due to a lack of knowledge, a large number of farmers use overdose pesticides in rice plants by identifying diseases manually which results in the reduction of quality rice production. If the identification of the fungal disease in rice plants is not addressed timely, it might damage the entire crop production of our country. The recognition of fungal disease is one of the most challenging tasks for rice cultivation. Executing these tasks manually using traditional methods such as visual examination can lead to human error and time-consuming and need experts for solutions. The disease harms crops of all stages and the average loss is approximately 28-36% which can be increased up to 80-100% based on different areas[13]. Fungal diseases can easily affect every type of rice plant which is a leading threat to food security. The failure of a crop in a cultivating period due to fungal disease may bring immense suffering to the common people. Thus, early detection using several image processing technologies will help farmers with effective crop management and better rice production. Due to the enormous negative consequences that diseases have on rice plants' health and agricultural output, a deep learning-based system that can accurately and efficiently diagnose illnesses in rice plants is vital. At first, emphasizing the importance of human intelligence in the complicated, multi-step processes of agriculture is necessary. Then highlights the difficulty in diagnosing illnesses in the absence of primary information or basic understanding. Then, explains the shortcomings of the current visual examination techniques, including their time requirements and competence requirements. It is necessary to identify the fundamental barriers as being the creation of a trustworthy, efficient, and automated deep learning-based system for rice plant leaf disease diagnosis. This issue statement lays the groundwork for the creation of a solution that uses deep learning technology to precisely and quickly identify diseases in rice plants in order to address these agricultural difficulties.

1.3 Research Objective

Our research articles primarily aim to assist our dedicated farmers and maintain their commitment to advancing computer vision. The fundamental objectives of our innovative research are,

- Design an effective method to identify affected rice plant by fungal disease through image processing and applying neural network models.

- Collecting new data points on “False Smut” to create an authentic dataset which will bring new point of view for future research.
- Select deep learning techniques used by other researchers and compare their performance with the approach used in the rice fungal disease detection task to understand the completion of deep learning models used for this task and decide the most appropriate methodology.
- Design a web application for the diagnosis of fungal diseases in rice crops: Simple screen-based system for farmers. Develop knowledge about building applications for the mobile platform, particularly the need for an opportunity to use this technology in solving real-world problems in areas such as farming.
- Providing modern technology for the farmers as still in this country the farmers use old technology and because of that we lacking in production of crop.
- Providing a system for farmers who lives in the distant part of the country to identify the disease that affected their plants as the number of experts in the field are very few and they can not provide services every where all at once.

Chapter 2

Literature Review

In[1], The author showed that 70% of the people in India are dependent on the agricultural sector, which grows a variety of fruits and vegetables. Although monitoring perennial fruit crops and cotton's renown as the "White Gold" help the textile sector, technology can enhance agriculture. The analysis of digital pictures captured by mobile cameras employing RGB pixels enables farmers to make educated judgments about diseases and pests, enhancing output and lowering yield loss. The article discusses a leaf picture that was segmented using color filters and RGB pixels and then rendered in grayscale. White lightning represents the illnesses that are afflicted and are created by edge detection utilizing Canny and Sobel algorithms to determine the sharpness of edges. Instead of using a 3x3 pixel dimension the dissimilarity edge detector uses the dissimilarity of adjacent pixels. The outcome is divided using the homogeneity-based edge detector.

In[2], Number of increasing human population is driving up demand for rice, a vital cereal crop in Kashmir. Cultivated in temperate and sub-temperate regions, hill rice cultivars have limited genetic variability. In Kashmir, breeding operations have reached a point of diminishing returns. Should climate change turn unfavorable, productivity could plummet dramatically. Smut disease is another constraint and threat to rice production in Kashmir because of the unique agro climatic conditions. Growing number of people leads to growing demand of rice – an important cereal available in Kashmir. Hill rice is a cultivated type of low genetic diversity of cultivated temperate and sub temperate regions. There is already a saturation point in the breeding activities taking place in Kashmir. When climate changes for the worst, production may go down severely. Estimates of the disease's impact on grain yield loss range from 0.2 to 49%. Because of the agroclimatic conditions in Kashmir, rice fake smut poses a new threat to the region's rice crop. Chlamydospores turn dark green or black as a result of the disease, which causes infected grains to enlarge into velvety green masses. In order to determine the frequency and severity of the disease, this study carried out a thorough survey in the districts of Kulgam, Anantnag, Pulwama, Budgam, and Srinagar during the months of Kharif 2010 and 2011. The highest incidence was found in Budgam (22.2%), followed by Kulgam (13.2%). Analogous occurrences in China and India have been documented in earlier research. During the 2010–2011 Kharif seasons, tests were initiated to regulate the sensitivity of commercial cultivars and genotypes of rice to false smut. The findings indicated variations in the frequency and intensity of the disease, with the commercial cultivars Jhelum and Shalimar Rice-1 exhibiting resistance. Cultivars of rice contributed significantly to the fake smut infestation. In the 2010–2011 Kharif seasons, tests were conducted on commercial varieties and genotypes of rice for fake smut susceptibility. The resistance of Jhelum and Shalimar Rice-1 was discovered, underscoring the important role played by rice cultivars.

In[3], For categorizing of maize leaf diseases using local and global characteristics, is proposed using a modified LeNet architecture. According to the study, 3-9-3 kernel size is ideal for classifying maize leaf diseases. Other plant leaf disease categories, such as those affecting maple and hydrangea leaves, can be made using the suggested CNN. The system is split into two phases: training using artificial neural networks, feature extraction, picture capture, preprocessing, and Fuzzy Logic Toolbox, and testing using this toolbox. For photos of leaves with Leaf Spots and Leaf Scorch, the algorithm creates clusters. By using the recognize push button, the user may identify the input leaf. Based on characteristics generated in the GLCM matrix, the disease recognition component names the disease. 11 parameters are calculated by the leaf recognition module: smooth factor, form factor, median, skewness, and standard deviation. For automatically identifying and rating leaf flaws, an artificial neural network (ANN) and machine vision technology system is developed. This effective method can take the place of manual leaf recognition and assist agricultural professionals in determining the right pesticide and its dosage.

In[4], A crucial aspect of Bangladesh's social and political stability is its dependence on rice as a staple diet. Bangladesh is an agro-based nation. Even if rice production has reached self-sufficiency, the nation still faces difficulties as a result of diminishing resources and growing susceptibility to climate change. Bangladesh's rice yield is contrasted with those of nations like South Korea, China, and Japan. A major biotic factor that affects rice productivity is disease, which costs the crop 10–15% of its annual output. The frequency of rice fake smut disease was the study's main emphasis as it surveyed farmer's fields in Bangladesh's northwest. A sampling of ninety fields from four unions showed substantial disease heterogeneity and diversification. The frequency of rice fake smut disease was the study's main emphasis as it surveyed farmer's fields in Bangladesh's northwest. A sampling of ninety fields from four unions showed substantial disease heterogeneity and diversification. The fungal infection frequency, number of smut balls per infected panicle, and yield loss differed substantially across the nine surveyed unions in the research, which examined 90 fields in the Natore area of Bangladesh. The frequency of rice false smut disease varies geographically, with certain cultivars being more resistant than others. While transplanting time and genotype manipulation are examples of management strategy, strategic management has not yet been studied in Bangladesh. The study, which is a component of the author's master's thesis, is centered on plant pathology and seed science and involves field selection and survey support from agricultural officials.

In[5], The paper presents a deep learning neural network model called DICMTLM and Softmax activation function to enhance classification and implement image processing. In this research paper, the author used a data set that contained three features of diseases and they are Bacterial leaf blight, Brown spot, and Leaf smut. Convolutional Neural Networks (CNNs) like GoogleNet, AlexNet, and ResNet are used to extract essential features. The model achieves an 82.2% to 78.5% accuracy rate, compared to 78.3% to 71.2% for existing methods. The false-positive ratio is also reduced, and space complexity is reduced by approximately 24 MB. However, the study's limitations lie in the dataset size, necessitating further research on larger datasets.

In[6], To produce high-quality, high-yield maize, maize diseases are essential. For sustaining high yields and quality, illness detection employing genetic algorithms, SVMs, artificial neural networks, and deep learning is crucial. To categorize maize leaf diseases, methods such as color, texture, and morphological characteristics have been devised. The 3852 photos from the PlantVillage dataset, a gradient-descent technique, and a new approach for classifying maize leaf diseases are used in this study. Using the PlantVillage dataset, the CNN model is used to identify the maize leaf disease, with increased classification accuracy for the balanced dataset. With kernel size 3-9-3 performing better than other kernel sizes, the modified LeNet architecture is suggested for diagnosing maize leaf diseases utilizing local and global information. Other plant leaf diseases can be categorized using the suggested CNN.

In[7], The authors highlight the importance of plants for energy and global warming solutions but also emphasize the requirement to detect early and manage plant diseases. The study uses radial basis function neural network (RBFNN) classifiers for detecting plant leaf diseases, with an accuracy rate of 95%. This method can significantly reduce crop yield loss and contribute to cost-effective disease management, as it can be upgraded to detect and quantify diseases. The study provides a comprehensive approach to early detection and management of plant diseases.

In[8], Early distinguishing and categorizing of crop plant diseases is crucial for agricultural practices, preventing product loss and improving product quality. Traditional methods require subjective visual symptoms or laboratory identification, which can be time-consuming and require professionals. Deep learning techniques like transfer learning have shown high performance in various fields. This paper is used for training on rice plant disease, AlexNet, a pre-trained deep CNN model, extracts visual characteristics from earlier levels. Utilizing AlexNet and SVM for the classification of rice illness and the MatConvNet toolkit for implementation, the study investigates transfer learning in deep CNN. Three training-testing partitions are used to divide the dataset into training and testing sets: 60%-40%, 70%-30%, and 80%-20%. For 80%-20% training-testing partition, the paper achieves 91.37% accuracy.

In[9], The authors highlighted Rapid illness spread makes disease identification difficult. It is vital for society's awareness that image processing and machine learning methods like filtering, the CLAHE algorithm, and SURF are utilized in agriculture to identify illness. The suggested work improves rice leaf recognition accuracy by utilizing effective machine learning and image processing approaches. It is implemented in MATLAB version r2015a. According to the study, SVM with LBP, Linear, Polynomial, and RBF functions produces an accuracy of 89%, 90.23%, and 86.21%, while SVM with HOG produces an accuracy of 92.01%, 94.6%, and 89.0%.To help farmers save early crops, the suggested method employs SVM+HOG with a polynomial kernel function to identify illnesses affecting rice plant leaves.

In[10], A common crop in Asia, Africa, South America, and the US, rice is sensitive to several pest and disease outbreaks, including RFS (Rose Fever Syndrome). RFalse smut (FS) decimates rice crops by causing fungal infections and resulting in yield losses. It is caused by the fungus Ustilaginoidea virens. Disease diagnosis has improved thanks to recent developments in computer vision and machine learning, which use methods like discriminant analysis, K-Nearest Neighbors (KNN), and SVM. Techniques for automatically diagnosing rice diseases in wheat, maize, cotton, and tomato crops have been developed. However, segmentation, feature extraction, and limited data processing are some of the drawbacks of classic machine learning approaches. CNN has been used in many different domains, such as video analysis, picture classification, and object detection.The ensuing subsections contain specifics on the methods used to identify RFS. The research trains a CNN model using rice bogus smut photos taken from rice fields using a 48 Megapixel smartphone camera. The pictures are tagged with the fitting of the faux smut affected region and scaled to 227x227x3. The primary train algorithm workspace receives the exported ROI labels. The second sub-network predicts the actual class of each proposal, and the RPN is utilized to train for proposal creation. Three distinct photos of panicles are used to evaluate the model: an immature, healthy panicle, a mature, healthy panicle, and a fake, smut-affected panicle.

In[11], The author proposed a paper that highlights the importance of rice plants in global crop production. Through image and neural network processes, this paper aims at the topic of disease detection in wetland areas. Rice plants are susceptible to diseases caused by fungi, bacteria, or viruses, which vary by region. The study creates two classes of images for diseased and healthy plants, focusing on four stages: image preprocessing, Otsu segmentation, GLCM extraction, and classification. The final stage uses a Probabilistic Neural Network (PNN) to determine the plant's health status. A Matlab program detects diseases using a GUI, image preprocessing, segmentation, GLCM algorithm, and PNN for classification. The model achieves 82.09% accuracy for diseased plants and 71.64% for healthy ones. Future research should explore different models, image pre-processing, feature extraction, segmentation algorithms, and deep learning approaches using different camera technologies.

In[12], Production has been severely reduced by fungal infections, particularly illnesses that affect walnuts. Common issues with walnut trees include anthracnose, leaf blotch, and bacterial blight. Between 2000 and 2017, these issues significantly reduced productivity. For diagnosing and classifying walnut leaf illnesses, the suggested technique utilizes a leaf picture, pre-processes it, segments it, extracts its characteristics, and feeds those features to a classifier. There are five modules in the architecture. In order to forecast walnut leaf illnesses including anthracnose and blotch, the study analyzed pictures of walnut leaves and extracted characteristics using GLCM and color moment. Thirty percent of the 3670 photos were utilized for testing, while the remaining 70 were used for training the model. The collection contained 515 photos of healthy leaves, 740 images with blotches, and 2415 images of anthracnose-infected leaves. On the test dataset, the trained model was put to the test to see if it could identify walnut leaf diseases. The detection and classification of fungal infections in walnut leaves using machine learning are presented in this research. The technique performs input picture preprocessing, YUV color space conversion, Otsu thresholding segmentation, and feature extraction for color and texture. 70% of the photos are used for training and 30% for testing the model. According to experimental findings, the BPNN model performs better than the mSVM in classifying and identifying walnut leaf diseases. This method of disease detection can be used by farmers.

In[14], The economy of India heavily relies on agriculture, with meteorological and biological elements having an impact on crop growth. Crop disease is a significant biological component that affects yield reduction, and automated identification is necessary for prompt action. With an emphasis on object detection and classification, a fully linked Convolutional Neural Network (CNN) framework is suggested to extract features from input photos. The approach employs classifications for brown spot stages of early, developed, and healthy rice leaves. An input layer, several convolution and pooling layers, and full connected layers are used to build the network. The model learns better thanks to the generated dataset, which achieves 100% accuracy for healthy classes and 98.5% for brown spots in the early and advanced stages. Recall rates for courses with no early-stage brown patches are 100%, 99.5%, and 95.4%, respectively. With a training duration of about 20 minutes and 17 seconds, the model is quick and precise. Early diagnosis of brown spots enables farmers to take preventative action and lowers pesticide consumption. The system may be improved such that it can identify other illnesses in paddy at an early stage and categorize them using different plant data.

In[15], Two persistent diseases that seriously reduce grain yield and quality in rice are kernel smut and fake smut. In the United States, the growing use of vulnerable cultivars, nitrogen fertilizer, and short crop rotations have caused these once minor diseases to become commercially significant. Cultivated in more than 100 nations, rice is the third most popular cereal crop worldwide, with the US being a major producer. But a major worry these days is the disease known as kernel smut, which lowers rice grain quality and yield. The disease is common in practically every nation that grows rice, while several nations, including the United States, have banned the sale of smutted rice. False smut outbreaks increase the incidence and yield losses globally, costing rice growers a substantial amount of money and producing mycotoxins that can have a negative impact on livestock and human health. Even though there isn't a stated maximum incidence allowance, fake smut can still be a big problem. Rely upon the weather condition and rice cultivar, false smut can result in yield losses of 3 to 70%. There is no cap on the proportion of rice contaminated by fake smut, in contrast to kernel smut. The false smut fungus produces two different kinds of mycotoxins. When rice grains and straws are contaminated with mycotoxins, it can be harmful to both human and animal health and cause cancer. False smut symptoms resemble powdered chlamydospores instead of rice kernels and are evident outside of the kernels. generates sclerotia and chlamydospores when it infects rice blossoms, and it can sustain high germination rates for up to five years.

In[16], Six different plant diseases were classified using DenseNet201 and AlexNet. The model can differentiate between healthy, bacterial leaf blight, narrow brown spot, brown spot, leaf scald, brown spot, and leaf blast. In order to increase the amount of data points and improve the data quality, augmentations were undertaken. On non-normalized, normalized, and supplemented datasets, the models were put to the test. Performance was measured using evaluation matrices like accuracy, precision, recall, specificity, F1-score, loss function, and confusion matrix. For non-normalized, normalized, and augmented datasets, DenseNet201 attained an accuracy rate of 89.86%, 88.33%, and 83.41%. For the non-normalized dataset, VGG19 had the greatest accuracy 96.01%, whereas GoogleNet had the lowest. The study effectively proved the modified transfer learning method based on VGG19's accuracy.

In[17], Rice, a crucial global crop, faces increasing consumption in China and India, with Russia relying on agrochemicals for food and medicine. Diseases and pests cause production losses, posing environmental and pest concerns. Researchers consider four fragile models for this research they are GoogLeNet, ResNet, SqueezeNet, and DenseNet. DenseNet-121 outperforms other models in accuracy, precision, and recall, with GoogleNet and SqueezeNet as the best performers. DenseNet-121 achieved the best accuracy with 95.57% accuracy on the validation dataset. However, internet data training makes the model's generalization ability uncertain. The study uses neural networks to explore rice fungal infection identification, comparing classical and contemporary architectures. Effective data collection and preliminary marking-up processes can automate diagnosis, and the optimal architecture resists change.

In[18], This study presents an AI-based approach to categorize rice plants' fungal and bacterial diseases. Several models include SegNet, RPK-means clustering, Handmade CNN (HCNN), and UNet. They utilized a dataset from Chhattisgarh, a state in India, including 1500 images captured using a high-resolution DSLR camera. The dataset contains six classes, including 250 pictures of the disease named rice blast, 300 pictures of leaf scaled, 200 pictures of sheath blight, 250 pictures of brown spot, 250 pictures of normal leaf, and 250 images of leaves affected by bacteria. The accuracy of the HCNN model for RPK means the preprocessed image is 96.88%, and for the k-means processed image is 95.42%. Compared to the UNet model, the SegNet model shows 3-4% higher accuracy

In[19], The author introduces an innovative approach Using deep learning techniques to create a system for the early recognition of illnesses affecting rice plants. For categorizing 12 different illnesses and malnutrition, they employed a dataset of 2259 smartphone photos and 250 instantly taken photographs. For performance evaluation, the researchers employed 11 deep learning models, including stochastic depth optimization and freezing convolutional layers. The quickest among all mobile devices was MobileNetV2, whereas DenseNet 201 had the greatest AUC score of 0.9909 overall. The Xception model had a training time of 6320.95 seconds, making it the slowest. The best models for cloud-based architectures and smartphone apps were ResNet50 and MobileNetV2. The study illustrates a practical and effective method for identifying rice plant diseases.

In[20], The author proposes a novel approach that uses image processing techniques and classifies rice plant diseases. The research focuses on the early detection of blight and brown spots, which are rice plants' significant bacterial and fungal diseases. The researchers used a dataset containing infected rice leaf images collected from different environments. The study discusses enhancing the input image quality, transforming the color through HSV color space, and achieving the segmentation using k-means clustering. The methods represent a successful approach to automated rice plant disease spot identification and early prediction. The proposed method is completely automatic and efficient within a small dataset.

Chapter 3

Dataset

3.1 Data Acquisition

In this research to detect infected rice by the fungal disease known as false smut, a custom dataset has been constructed from a sample of healthy and infected rice plant leaf images. The dataset is collected from a village named Navaron under Sharsha Thana in Jessore district where people's main source of income comes from agriculture. Amal Karishna Paul, an excellent and optimistic Sub Assistant of Bangladesh Krishi Somprosaron, Sharsha, Jessore helped to identify the disease and collect the pictures with his expertise in the field. To collect clear images with high resolution, a DSLR camera Canon 1300d and a 50mm prime lens are used for better image quality. The dataset contain overall 991 pictures of 18MP image resolution of 5184x3456 pixels including two classes of healthy and unhealthy rice plants from the category named Hybrid Amon 17. The pictures given below are the healthy and unhealthy images from the dataset.

(a) Healthy Rice Plant of Hybrid Amon 17

(b) False Smut Rice Plant of Hybrid Amon 17

Figure 3.1: Healthy and Unhealthy images

The unhealthy class has 539 images of affected paddy sheaf named Rice False Smut. The healthy class belongs to the sample of healthy paddy sheaf consisting of 452 images in JPG format. Each picture was identified by the agriculture expert officer Amal Karishna Paul.

This research's main focus is to detect the vital bacterial disease False Smut in rice plants. For efficient working on this topic, the research utilizes a unique dataset. The dataset present in the internet are not suitable as well as do not contain enough data. As the research focuses on binary classification, collecting suitable dataset from data repository is very difficult at the same time comes with several issues as follows,

- Enough images of the target disease were not available
- The picture quality of the available images was not good enough
- The labeling of the pictures was not appropriate
- The Rice plant specifically Hybrid Amon 17 did not have pictures of the disease
- The Pictures had different backgrounds which can cause a lot of problems when the models are being trained

These were the main problems we faced during selecting a dataset. So with the help of a generous person Amal Karishna Paul we made the dataset and the reason for making a specific dataset was:
The key perspective to create the dataset is to work on the Hybrid Amon 17 rice plant to provide valuable information that can help agricultural progress.

- To ensure data Quality. The dataset used in the research has high-resolution pictures and similar backgrounds. These two things impact greatly in the learning phase of a model.
- Datasets that are used in the research need to have the same amount of data in the classes that are present.
- The research focuses on the development in computer vision and to provide help to agriculture. And to satisfy these two requirements we came up with our own dataset.
- The problems we mentioned earlier in finding the dataset are the reason to came up with this dataset which has a specific type of pictures and high-quality of images. Most importantly the images are verified by an expert working in the field.
- The existing dataset lacks the augmentation and the quality which can be the preprocessing that can be applied for this specific research. So to have the data and run the way we want made us motivated to make this dataset.

In research, we need a dataset and have to rely on the data to carry on our research. Working on an existing dataset may not bring variety in research and new information. So, to keep a great contribution and provide the world with new sets of data to bring more advanced impact by the next generation was the main goal behind creating this dataset.

3.2 Data Preprocessing

For deep learning-based image classification, data preprocessing is a crucial step as raw images can exhibit variations of image resolution, aspect ratio, color channels and pixel intensity distributions. The variations can affect the performances of deep learning-based methods. For that reason, it is required to apply preprocessing techniques to ensure consistency and compatibility with the input requirements of the models. The images of our custom dataset vary in resolution and aspect ratio. To ensure the consistency and comply with the input size, all images were resized to a certain size of 224x224. Along with the parameters from the above mentioned table

Target size	**Batch Size**	**Rescaling size**	**Train**	**Test**	**Validation**
224x224	32	1/255	70%	20%	10%

Table 3.1: Parameters for Augmentation

we have also used some other variables while doing augmentation on the dataset before running the model:

Horizontal Flip	**Rotation range**	**Width shift range**	**Height shift range**	**Shear range**	**Zoom Range**
TRUE	30	0.3	0.3	0.3	0.3

Table 3.2: Variables used for Augmentation

To handle the different dimension of each picture, images were resized in 229x229 for InceptionV3 and 224x224 for the rest of the models. Data augmentation refers to the modification of existing data applying several techniques which help to train the model properly and give accurate results. As the dataset is imbalanced, augmentation is essential to achieve accurate efficiency. Several augmentation techniques are used for this research such as Rescaling size, Horizontal Flip, Rotation range, Width shift range, Height shift range, Shear range, Zoom range. These techniques help the model to understand the input pictures better and based on that it can learn better which ensures better accuracy. With these techniques applied on the dataset the models are utilized and the research achieve the information for critical analysis among the models capability on the dataset which are mentioned in detail in the analysis part.

3.3 Class Categorization of Rice Plant Images

Deep learning models, specifically CNN models have exhibited a remarkable success in image classification and pattern recognition. The dataset is split in train, test and validation. This study adopted binary classification in our custom dataset. Among all images the training part is split to 70% , testing is 20% and validation is 10%.
Our research followed a structured workflow to attain effective training and evaluation of the Convolutional neural network models. The workflow consists of training, testing and validation phases. The image data plays a crucial role as the input to

Train	Test	Validation
712	199	80

Table 3.3: Splitting Datasets for Optimal Learning and Generalization

deep learning models which enable the models to learn and make accurate predictions. So, the train part is for when the model is learning from the data we have given and tries to understand what information it is getting. Then comes the testing part, here we use different sets of data than data used in training and try to identify the models performance and observe the progress with help of various metrics such as precision, accuracy etc. Finally the processing part ends with validation, with validation we can't truly say if our model is working fine with new information. Validation helps to justify the model.

Chapter 4

Description of the Models

4.1 Resnet50V2

This design is an advancement over InceptionResNet V2. The network may concurrently collect characteristics at various sizes thanks to this module. The network can collect characteristics at various dimensions and levels of complexity by employing parallel filter sizes, which enables richer presentation. Inception modules, on the

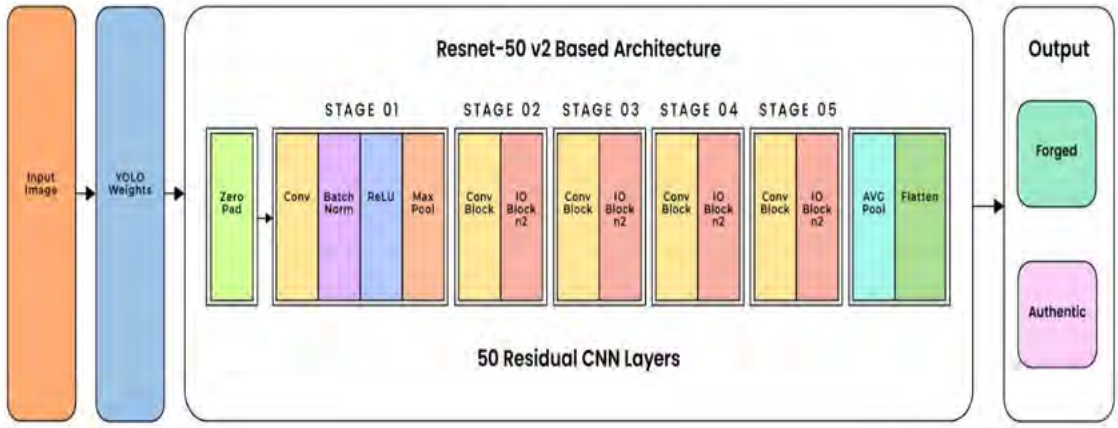


Figure 4.1: ResNet50V2 Architecture

other hand, are the essential part of the Inception architecture. Additionally, during the training phase, auxiliary classifiers are included to minimize the layers and lessen the issue of the vanishing gradient. Standard convolution layers are used in this module's first feature extraction step. Classification, object identification, and feature extraction are three common applications for this architecture

4.2 Alexnet

Convolutional neural networks (CNNs) like AlexNet are developed specifically for classifying images. Eight layers make up this structure: three completely linked layers come after five convolutional layers. Convolutional layers are in charge of extracting low-level to high-level representations by learning hierarchical characteristics from input pictures. ReLU activation functions add non-linearity, and the

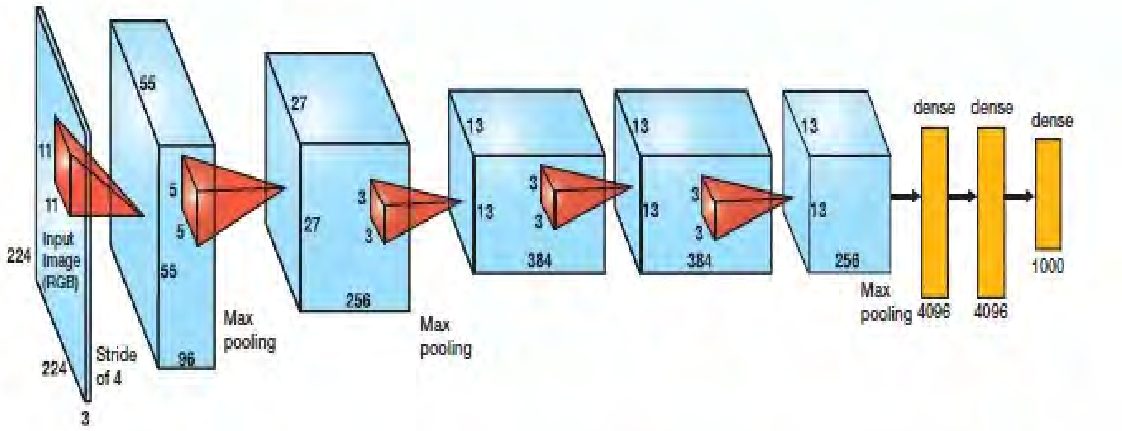


Figure 4.2: AlexNet Architecture

spatial dimensions are downsampled using max-pooling layers. The final output is produced by the fully linked layers acting as a classifier. To avoid overfitting, AlexNet additionally uses dropout methods. All things considered, it significantly advanced deep learning for image processing applications.

4.3 VGG19

Convolutional neural networks with the architecture VGG19 are intended for image processing applications. VGG19, created by the University of Oxford's Visual Graphics Group, is an extension of VGG16 that has a deeper structure with 19 layers. 16 convolutional layers with tiny 3x3 filters are among its primary characteristics. Max-pooling layers are then added to lower spatial dimensions. Three completely linked layers are also included in the architecture for categorization. VGG19 is a well-liked option for picture classification and related computer vision

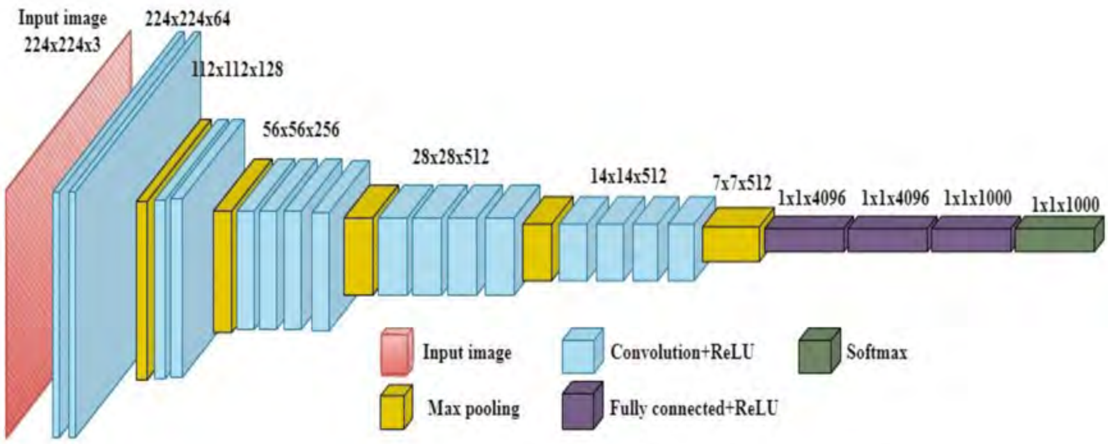


Figure 4.3: VGG19 Architecture

applications because of its simplicity and efficacy, as well as its ability to capture intricate elements in images. VGG19 uses multiple convolutional layers with 3x3 filters arranged in a sequential fashion. The design also incorporates max-pooling layers with 2x2 filters and a stride of 2 to reduce spatial dimensions and collect noteworthy information. These layers come following convolutional layers in a deliberate order. This layer structure helps with the hierarchical feature extraction process by progressing from low-level to high-level features as the data flows through the network. VGG19 begins when the image is entered into the input layer. The network consists of several convolutional layer stacks, each with a max-pooling layer and downsampling to maintain significant features. Convolutional layers are efficient feature extractors that take information and patterns out of the input picture.The most crucial characteristics are preserved while spatial dimensions are reduced with the aid of the max-pooling layers.

4.4 VGG16

The architecture of a convolutional neural network is VGG16. The University of Oxford's Visual Graphic Group (VGG) is the one developing it. There are three totally linked levels, thirteen convoluted layers, and sixteen layers total. This design consists of many convolutional layers arranged one after the other with a 3x3 filters. Furthermore, to lessen spatial dimensions and prominent features, max pooling layers with 2x2 filters and 2 are convolutional layers. At the conclusion of the network,

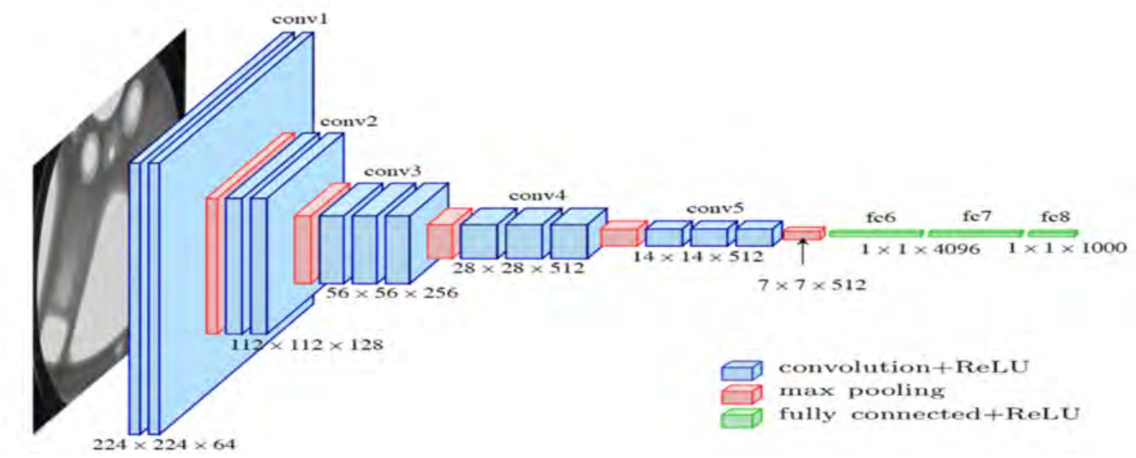


Figure 4.4: VGG16 Architecture

completely connected layers come after these. First, an input layer is used to start VGG16, where the picture is captured. Stacks upon stacks of convolutional layers make up the network. The max pooling layer comes after every stack. Convolutional layers operate as feature extractors, pulling low-level to high-level features from the input picture as the data flows through the network. Max pooling layers reduce the spatial dimensions of the feature maps, and pooling layers maintain the most important characteristics. At networks endpoint, the feature maps are flattened and routed through fully connected layers where they are classified based on learned features. Nonetheless, VGG's straightforward design and few convolutional layers make it simple to comprehend.

4.5 InceptionV3

This design is an advancement over InceptionResNet V2. The network may concurrently collect characteristics at various sizes thanks to this module.

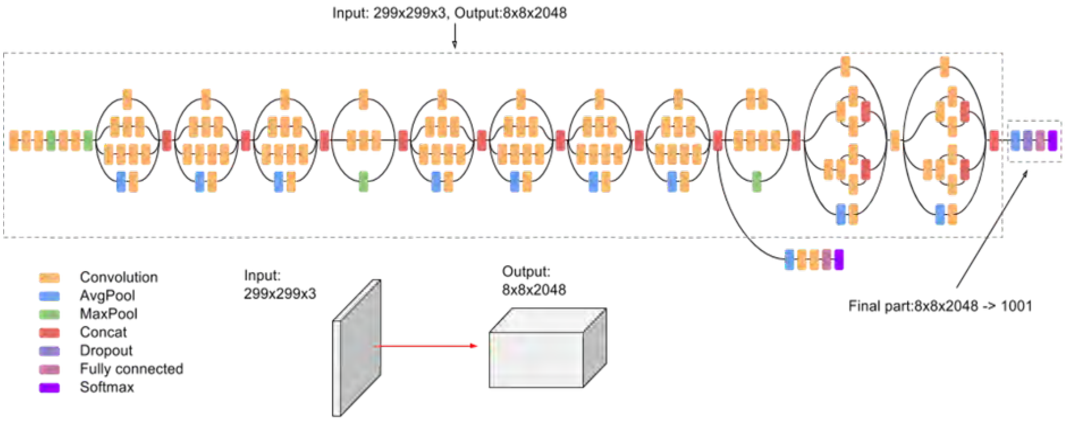


Figure 4.5: InceptionV3 Architecture

The network can collect characteristics at various dimensions and levels of complexity by employing parallel filter sizes, which enables richer presentation. Inception modules, on the other hand, are an essential part of the Inception architecture. Additionally, during the training phase, auxiliary classifiers are included to minimize the layers and lessen the issue of the vanishing gradient. Standard convolution layers are used in this module's first feature extraction step. Classification, object identification, and feature extraction are three common applications for this architecture

4.6 CNN

Convolutional Neural Networks (CNNs) automatically extract hierarchical information from input photographs, revolutionizing image processing. These networks scan

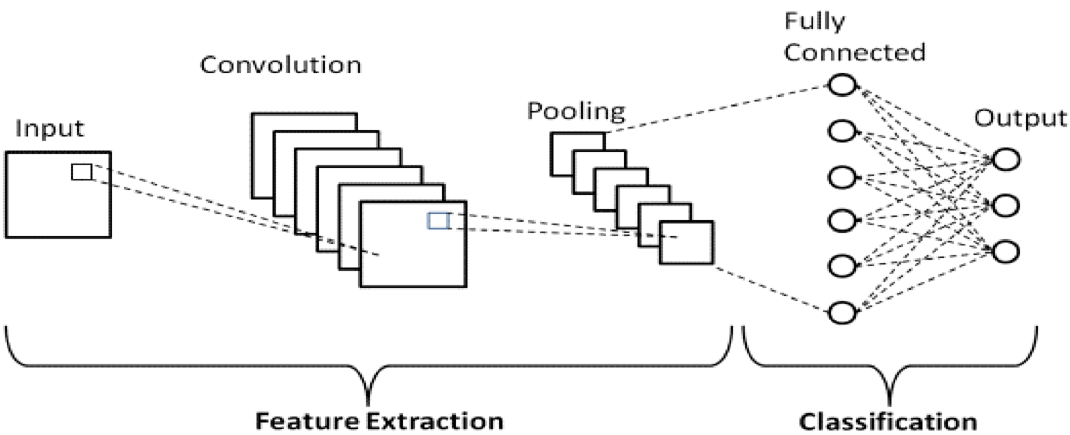


Figure 4.6: CNN Architecture

images and recognize textures, edges, and intricate patterns using small-filter convolutional layers. Non-linear activation functions, usually ReLU, add complexity to capture complex relationships. Max-pooling layers preserve crucial information while reducing feature maps to lessen the computational load. After flattening the features, the features are fed into fully connected layers, which function as a classifier to provide predictions according to learned attributes. Softmax activation is frequently used in the last layer to produce class probability outputs. CNNs are trained on labeled datasets, and during training, they use optimization methods to modify internal parameters and decrease prediction errors using back propagation. CNNs are a mainstay of contemporary computer vision, excelling in tasks like picture classification, object recognition, and segmentation thanks to its capacity to automatically learn and recognize complicated visual properties.

Chapter 5

Preliminary Analysis

5.1 Results and Analysis

In the experiment, several pre-trained CNN models are utilized for 10 epochs. CNN models including VGG19, VGG16, InceptionV3, ResNet50V2, AlexNet, and CNN model are used for classification.

Models	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**
VGG16	74.87	0.82	0.75	0.73
VGG19	79.39	0.81	0.79	0.79
Inception V3	98.99	0.99	0.99	0.99
AlexNet	89.44	0.89	0.89	0.89
ResNet50V2	96.48	0.97	0.96	0.96
CNN	92.46	0.93	0.92	0.92

Table 5.1: Model Evaluation Metrics Without using Augmentation

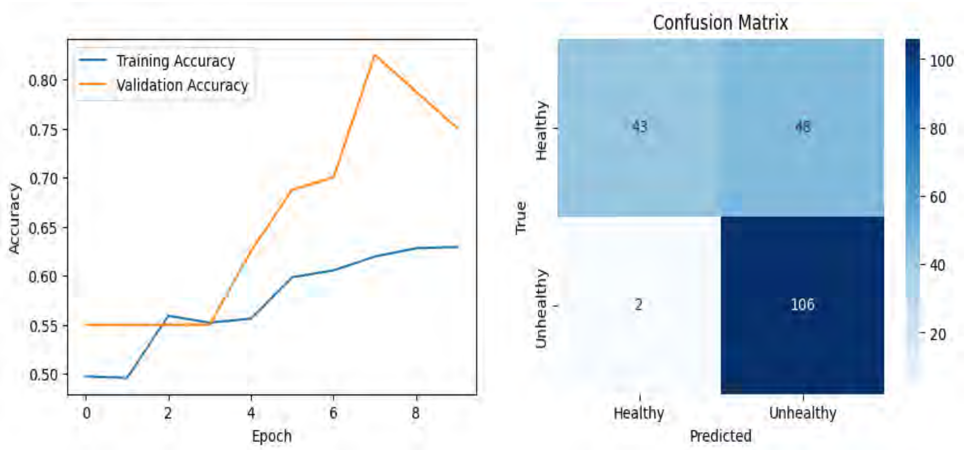
Among all the models, InceptionV3 performed well in both with augmentation and without augmentation classification. It achieved an accuracy of 99.49% using augmentation with precision, recall, and F1-Score 1.00, 0.99, and 0.99 respectively whereas without augmentation the accuracy is 98.99%.

Models	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**
VGG16	96.48	0.96	0.96	0.96
VGG19	97.98	0.98	0.98	0.98
Inception V3	99.49	1.00	0.99	0.99
AlexNet	90.95	0.91	0.91	0.91
ResNet50V2	93.96	0.94	0.94	0.94
CNN	91.46	0.92	0.91	0.91

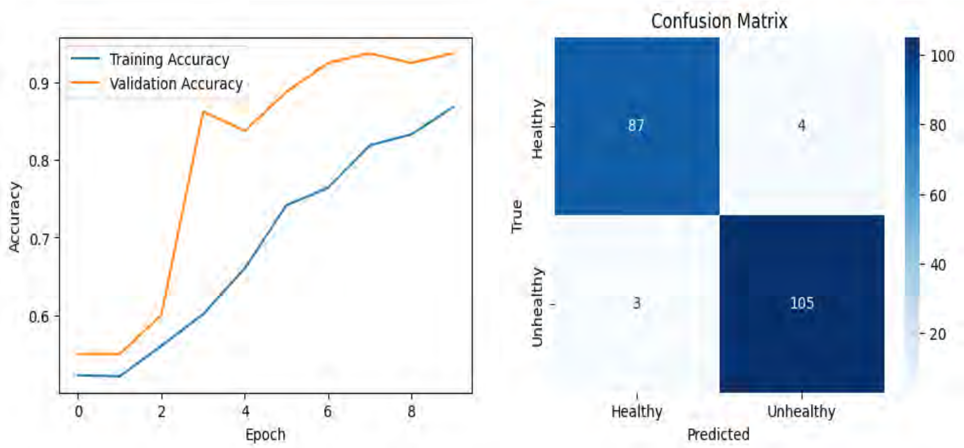
Table 5.2: Model Evaluation Metrics using Augmentation

Similarly, VGG16 achieved a lower accuracy without augmentation classification with an accuracy of 74.87% whereas with augmentation VGG16 achieved 96.48% accuracy. For AlexNet the accuracy without augmentation is 89.44% and it increased using augmentation achieving an accuracy of 90.95%. ResNet50V2 showed enhanced performance achieving an accuracy of 96.48% with using augmentation and 93.96% with augmentation. VGG19 also showed better performance compared to Vgg19, achieving 79.39% accuracy without augmentation and after using augmentation it gives a promising result with an accuracy of 96.48%. The CNN model had shown a promising permanence both with augmentation and without augmentation. It achieved an accuracy of 92.46% without augmentation and 91.46% with augmentation. The obtained results indicate that deeper architectures such as InceptionV3 and ResNet50V2 show accurate performance in the task of classifying rice false smut disease from images. Both their ability to capture detailed spatial features and acquire hierarchical representations helped them achieve very high accuracy, even without the help of data augmentation. The input size of InceptionV3 was also different from other models as it used 229x229 whereas other models used 224x224. Nevertheless, data augmentation played a significant role in terms of enhancing the performance of shallow architecture-based networks like VGG16 and VGG19 by closing the gap with deeper network models. By augmenting the training data towards greater diversity, these models could be better for generalization and learning the visual features in the images for classification. Nevertheless, like many other metrics, accuracy is quite popular; however, it is crucial to consider using precision, recall, and F1-score because the latter two offer a more detailed analysis, particularly for imbalanced datasets and situations in which false positives and false negatives are not equal in weight. According to the results, InceptionV3 was the most effective architecture for the task of rice false smut disease classification and the highest performance was demonstrated in terms of all evaluation metrics considering both types of images: with and without data augmentation. However, the ResNet50V2 also showed promising results making it a very reasonable option for practical deployment. The analysis helps in understanding the significance of effective deep learning designs and the use of data augmentation strategies to optimize image classification and specifically plant disease diagnostics to enable sustainable practices in crop cultivation.

5.2 Performance Analysis



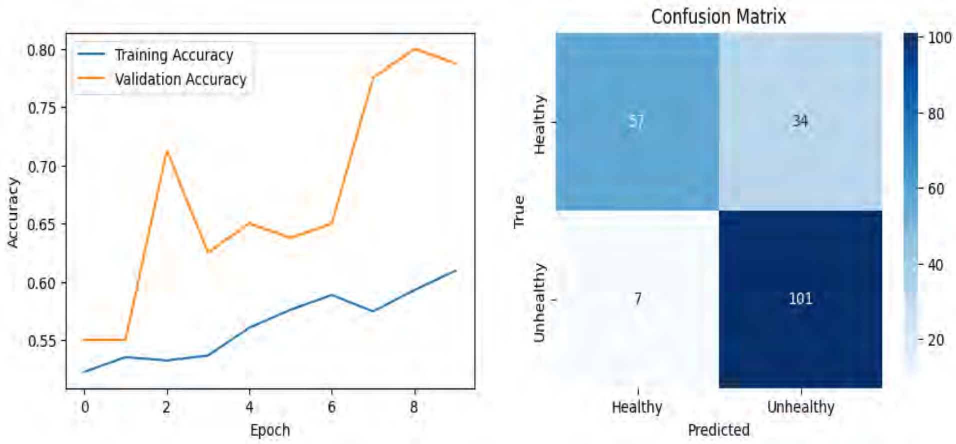
(a) VGG16 without Augmentation



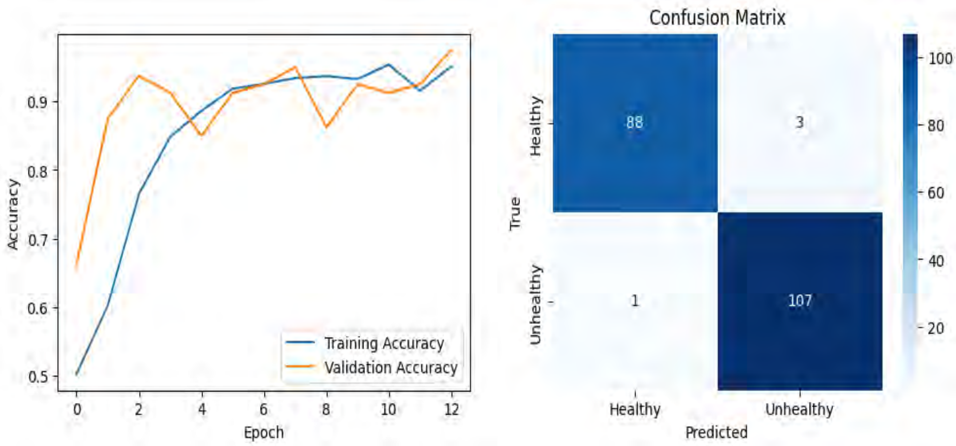
(b) VGG16 with Augmentation

Figure 5.1: VGG16 Confusion Matrix and Accuracy Graph

In the above graph 5.1(a), the accuracy gradually increases with the increase of the epochs and the confusion matrix represents 52 misclassified images without augmentation. Similarly, after using augmentation the accuracy in 5.1(b) is higher compared to the previous graph with 7 misclassified images.



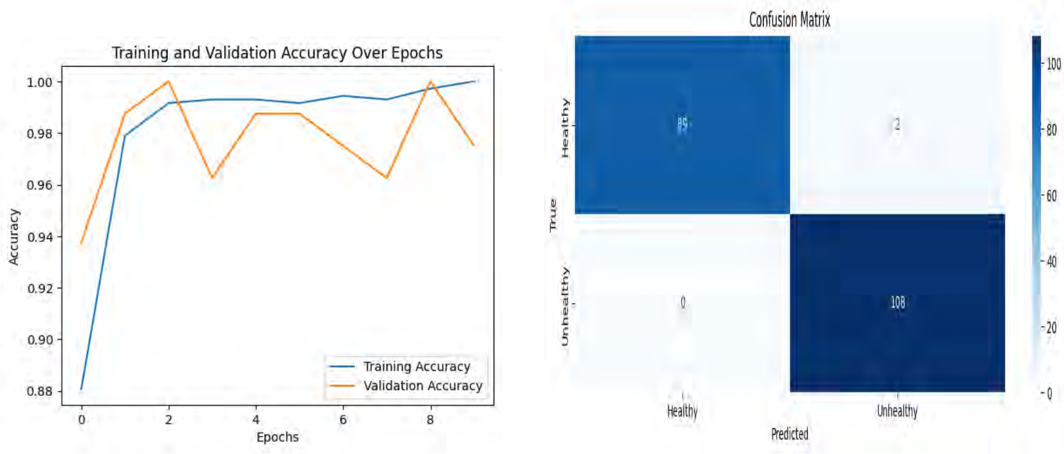
(a) VGG19 without Augmentation



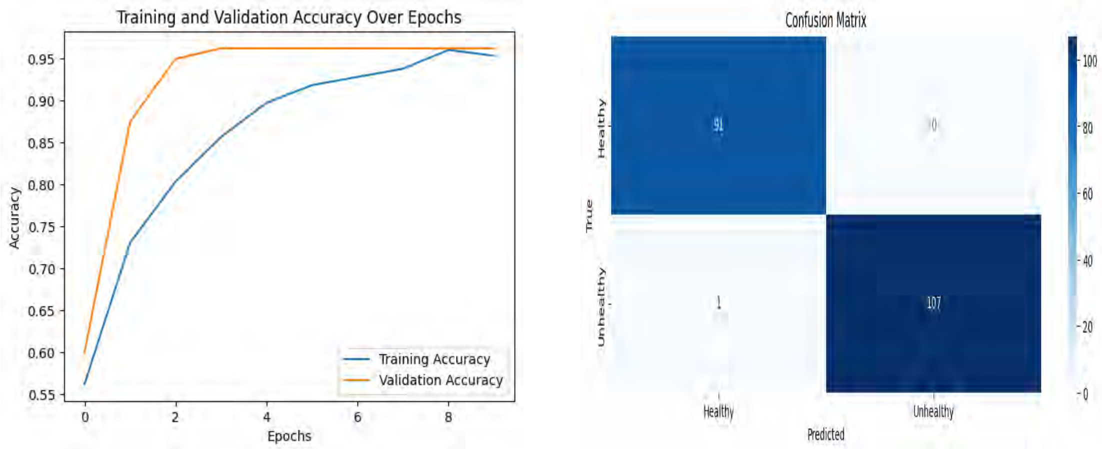
(b) VGG19 with Augmentation

Figure 5.2: VGG19 Confusion Matrix and Accuracy Graph

In the above graph 5.2(a), the accuracy increases at the beginning and then it converges compared to training accuracy the increase of the epochs. 41 misclassified images are shown in the confusion matrix without augmentation. Similarly, 5.2(b) represents the performance after using augmentation where the accuracy is higher compared to the previous graph and both training and validation accuracy are quite close with 4 misclassified images.



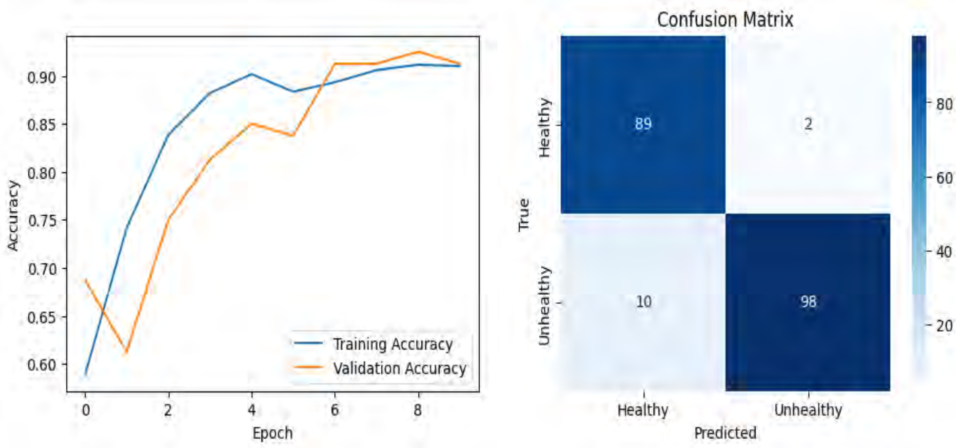
(a) InceptionV3 without Augmentation



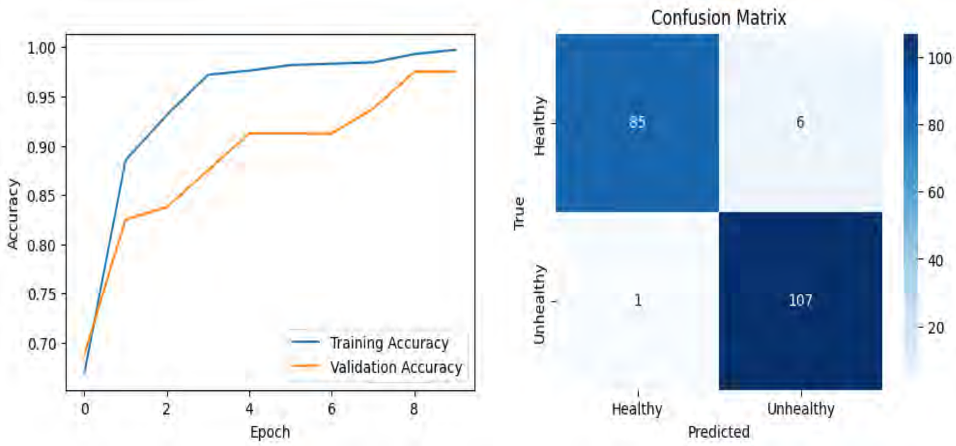
(b) InceptionV3 With Augmentation

Figure 5.3: InceptionV3 Confusion Matrix and Accuracy Graph

Figure 5.3 shows the accuracy in both without augmentation and with augmentation gradually increased with the number of epochs. The first confusion matrix shows 2 misclassified images whereas the second one increased to 1 misclassified image. The model performed best in our dataset.



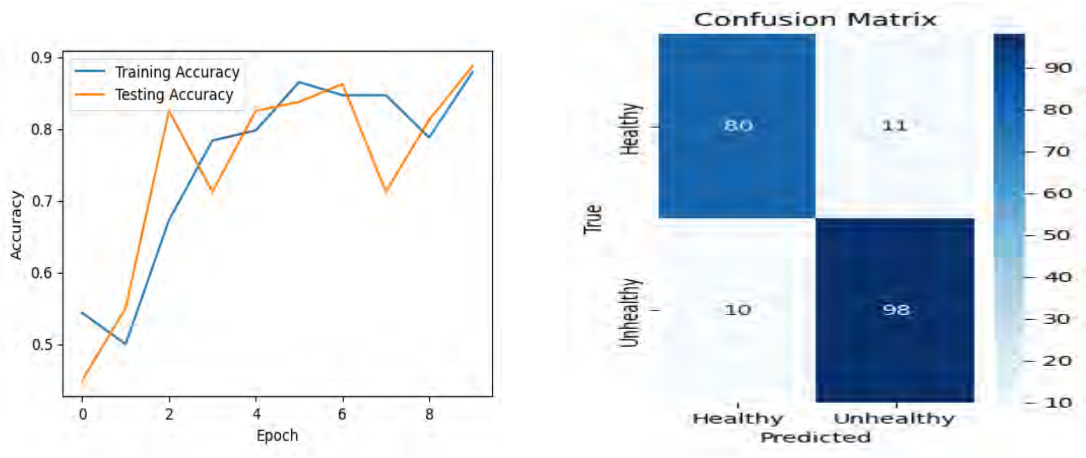
(a) ResNet50V2 without Augmentation



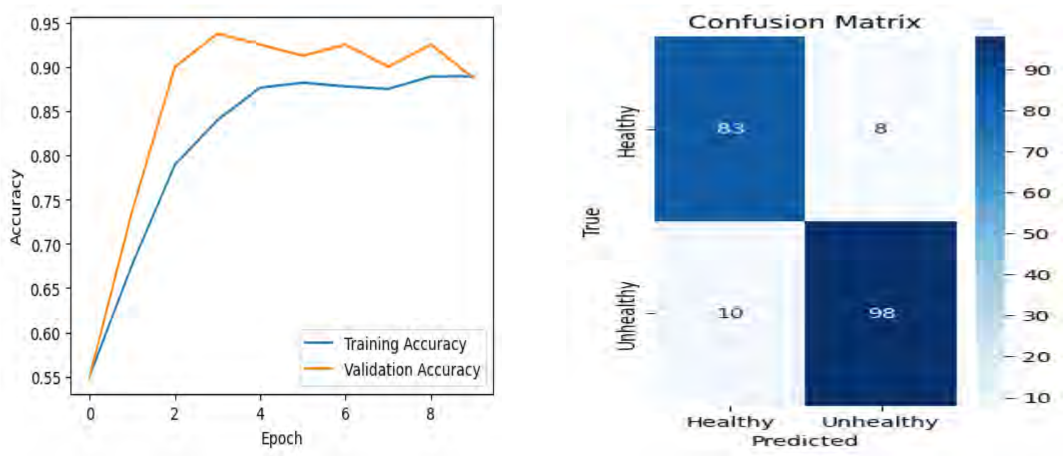
(b) ResNet50V2 with Augmentation

Figure 5.4: ResNet50V2 Confusion Matrix and Accuracy Graph

The graph without using augmentation shows a promising result of increasing rate in both training and validation accuracy with 7 misclassified images whereas the augmentation decreases the validation accuracy with 12 misclassified images



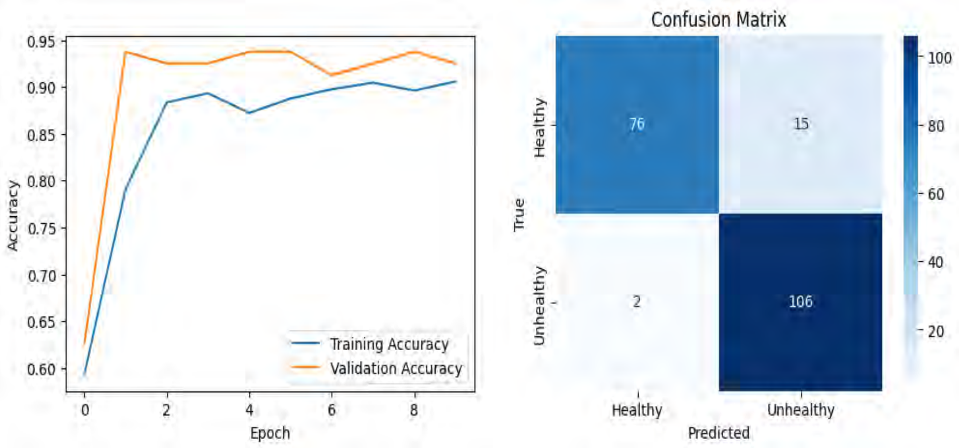
(a) AlexNet without Augmentation



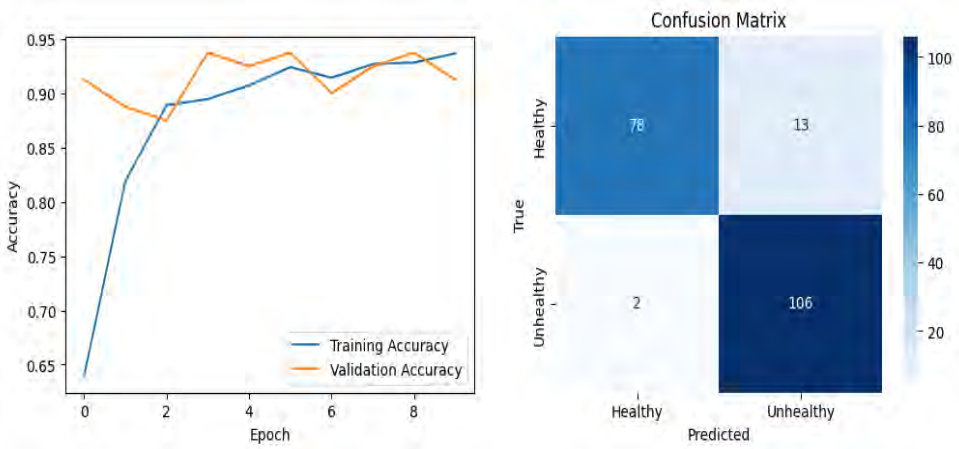
(b) AlexNet With Augmentation

Figure 5.5: AlexNet Confusion Matrix and Accuracy Graph

The figure above shows the accuracy in both without augmentation and with augmentation is gradually increases with the number of epochs. The first confusion matrix shows 21 misclassified images whereas the second one increased to 18 misclassified images.



(a) CNN without Augmentation



(b) CNN with Augmentation

Figure 5.6: CNN Confusion Matrix and Accuracy Graph

For the CNN both graphs show promising accuracy growth for training and validation. Without augmentation, the confusion matrix shows 15 misclassified images whereas the augmentation increased it to 17 misclassified images.

5.3 Explaining Model Decisions with LIME

As convolutional Neural Network models have demonstrated prominent performance in classifying images, their complex architecture often makes them difficult to interpret and understand. We employed LIME(Local Interpretable Model-Agnostic Explanations) to recognize the working of our trained models and point out those decision-related visual features that define the classification process. LIME is a technique that exhibits the individual prediction of machine learning and deep learning techniques. It works by observing small changes in initial input data and then tracing how these changes impact the model response. By investigating the alterations in the model's predictions, Lime can point out the most important and relevant features or regions involved in the final prediction.

(a) InceptionV3

(b) ResNet50V2

Figure 5.7: LIME Boundary Overlay for InceptionV3 and ResNet50V2 on Rice Plant with False Smut Disease

(a) CNN

(b) AlexNet

Figure 5.8: LIME Boundary Overlay for CNN and AlexNet on Rice Plant with False Smut Disease

In our study, we utilized LIME to our trained Convolutional Neural Network models to understand the visual explanation of the prediction on both healthy and 'False

Smut' affected rice plants. This kind of explanation is presented in the form of the boundary overlays; here the areas of the input image affected by the model's decision-making process are highlighted with red colors. Examining the LIME boundary overlays gave us extremely valuable data on the visual cues and patterns that the models used for accurate classification. The LIME boundary overlay visualizations for rice plants affected by false smut disease of InceptionV3 and ResNet50V2 models trained with data augmentation provide valuable insights for identifying their interpretability. In all the diseased plant images, the LIME overlays highlight the presence of smut balls which are presented as greenish-yellow or orange-yellow depending on the stage of the disease. The overlapping masks on the symptomatic areas exhibit the ability of these deep architectures to learn the right representative visual data that are associated with the false smut disease. It should be noted that these models were trained on images with a sufficient variety of data variations which helped them to gain the ability to generalize and define the visual feeders of the disease. The combination of data augmentation during training and the CNN and AlexNet models further allows the determination of the modest performance of the classifiers to identify rice plants affected by false smut disease. Though these models are able to point to the existence of smut balls in some cases, the overlays usually cover information near smut balls but not the smut balls themselves. This implies that these models may tend to use irrelevant or additional image clues like the ones mentioned above for classification rather than the optimal and normal visual features employed by models like InceptionV3 and ResNet50V2.

The LIME approach emphasize the inside workings of the models, helping in verifying that they indeed had the capability to capture the most significant visual features implicated in rice false smut diseases. Interpretability plays a critical role in building innovative instruments; it helps to ensure credibility and trust and also can suggest limitations and biases that could be of use in future builds.

Chapter 6

Web App Implementation

This research's main goal from the beginning was to make an application that will serve the people for the purpose of detecting affected or not affected rice plants. As mentioned in the analysis part the Inception V3 performed very well with an accuracy of 99.49%, precision of 1.00, recall of 0.99, and F1 score of 0.99. Also, the confusion matrix of this model was high with only 1 misclassification while using augmentation. So we have saved the model as an H5 file and implemented it in a Python web application. For this web application, Flask a Python-based micro-framework has been used. It is well known for its simplicity of setting up. Also, it does not require Object Relational Manager features but rather includes URL routing and template engineering. Flask is based on the Werkzeug WSGI toolkit and the Jinja2 template engine [21]. For the database part which is crucial for storing data, the built-in database system of Flask was used. For the frontend design of the web application HTML and CSS style was used. Also, TensorFlow has been used for the model to run on the web while input will be given to it. As the users will be mostly farmers so to make the website as simple as possible was the main goal while designing the website. That is why it is designed in the native Bangla language and the SPA (single page application) approach was taken.

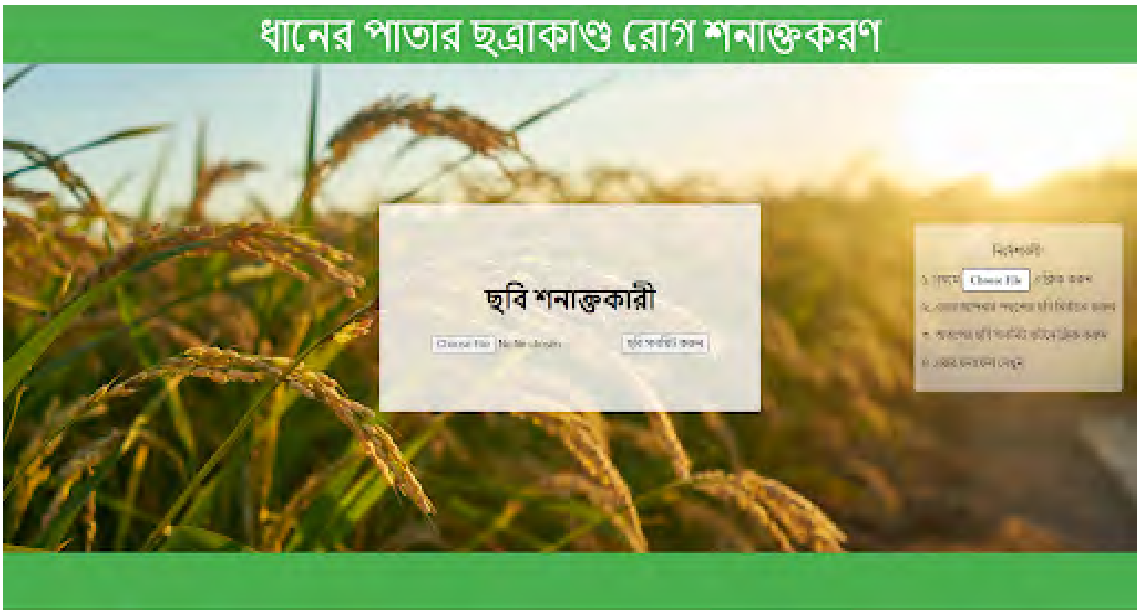


Figure 6.1: Home screen interface of the web app

Here, the user is welcomed with the symbol of green and rice which represents the golden age of Bangla. To operate the web application the user has to click the choose file button then the user will be redirected to the device storage the user is using. Then the user should select the picture that has been taken to know the result. After that, the user has to click 'ছবি সাবমিট করুন' button. Then the system will show the result as shown in the below Figure 6.2. In the backend to complete

Figure 6.2: Showing result of the given picture by user

the whole process Flask framework has been used as mentioned earlier. Here the 'render template' and 'request' methods have been used to render the template in front of the user and request to retrieve the picture that has been uploaded. When a picture has been uploaded it goes to the backend file named upload. Then the picture is pre processed and gets converted to an array to fit the model. After that, the model returns the result and the index.html page displays the result with the provided image. However, when the user visits the system the user uses the POST and GET methods for the whole process. When the user first visits the user sees the Choose File button and when it has been clicked a POST method is called which means the user will push something in the system. For example, we post anything on the social media platform is a perfect example of the POST method. After that, the pictures get into our database and then go to the model which determines the result. Finally, when it shows the result as shown in Fig 6.2 it uses the GET method to show the result.

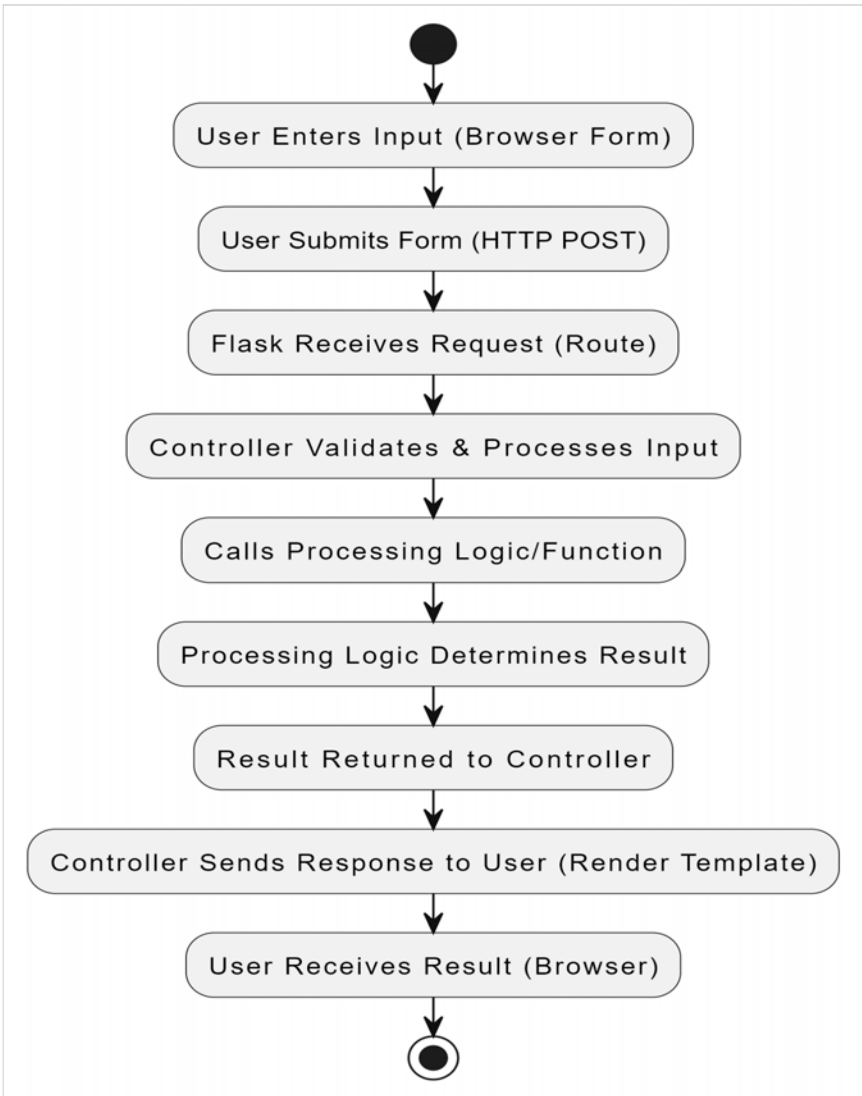


Figure 6.3: Web Application Architecture: A Flow Chart Breakdown

Here is a YouTube video of the web application has been demonstrated. To see the video click the following link:
https://youtu.be/5HbHktSBgPo?si=ePp0ORYvCv3Szz6J

Chapter 7

Error Analysis of Web Application

The website was developed for this research using the flask framework and the best performed model inceptionv3 in the backend and HTML as the frontend for the accurate classification of fungal disease in rice plants. After implementation of the website, plenty of images were tested on the website to understand the ability of providing accurate results. By analyzing numerous images, several limitations of the websites were identified. The inception model was trained on 452 healthy images and 539 "False Smut" affected rice plant leaf images. The web application performed well as the following figure 7.1 shows some of the results of the images that were tested during the process.

Figure 7.1: Accurate Results of affected rice plant images.

During the testing phase, some rice plants images were misclassified by the web application and the following figure 7.2 are the results.

Figure 7.2: Result of healthy images misclassified as unhealthy

As from the above figure it can be seen that the web application is denoting the given pictures which are not affected by the “False Smut” but are showing as affected. These misclassification can be cause for few reasons and they are:

- **Over saturated yellow color:** As the “False Smut” disease which occurs in the rice plant leaves are mainly of yellow and orange color. For example, the images in Figure 7.1 are affected by the fungal disease are the accurate results. But the images that are used in Figure 7.2 have over-saturated yellow color are misclassified. To justify this some images of crop fields were tested on the web application. As from the figure, it can be observed that even if the pictures were taken long distance from the rice plants it denoted the plants as safe. The reason for this result is that the pictures are quite natural pictures and in these pictures there is not an over-saturated yellow color. As the actual dataset contains unhealthy classes that contain false smut affected plant images that have a large portion of yellow color cast, the model might develop a bias towards associating yellow with false smut affected. Consequently, images that have incidental yellow lighting but are healthy as fig 7.2 shows might be detected as unhealthy due to the color association bias.
- **Representation in training dataset:** The quality and diversity of training dataset have an impactful influence on the performance of a model on new situations. The custom dataset used 712 images to train the model which contains insufficient images of long distance, blurred images and low quality for which the model might face difficulty in determining features and patterns

Figure 7.3: Accurate Results of healthy rice plant images.

that are needed to classify such cases during interference. Deep learning models are capable of recognizing the pattern and extract relevant features from the datasets they are trained on. So lack of sufficient images of long distance, blurred and low quality or contain variation on those images can result in the model's training performance to observe the distinguishing features and variation that may be present in those particular types of images. Consequently, when the model tested on such structures, it misclassified some images leading to poor performance.

- **Insufficient Model Capacity:** As ImageNet prioritizes high quality and clear images, pre-trained models like inceptionV3 can inherit bias from its training data and focus on features that work well in those scenarios. Thus, regarding the architecture and the number of learnable parameters the model may be lacking in one way or another, it would not be sufficient to explain the complex and finer details which are present in long-distance or blurred or low-quality images. Long distance, low quality, and coarse or blurred and unclear images are the types of images that we necessarily require more representation points to see or qualify precisely. If the model does not have enough capacity it may not be able to capture these and may come up with the wrong classification.

- **Resolution and Detail Loss:** In distance photos, the leaf surface may not be sufficiently detailed, making it difficult to discern minute differences between sick and healthy sections. The algorithm may generalize too much as a result of this lack of resolution, labeling healthy portions as sick.

- **Background Interference:** There may be extra complexity introduced by the backdrop against which the leaf is photographed. False positives in distance measurements might result from variations in the backdrop.

Chapter 8

Challenges and Future Work

8.1 Challenges

One the most crucial challenge that was encountered during this research was that enough data was not available publicly. Specifically, the data on 'False Smut' fungal disease were limited in numbers, images were not in high quality, and there were different backgrounds in every picture which were publicly available. So, it was quite difficult to select an ideal dataset to work on. Also collecting from the private owners of the photos was approached by us; it could not be done. Then the decision was taken to make a custom dataset. However, none of the teammates and the supervisors were experts in terms of hand experience to identify the disease as a trustworthy expert out of the team was needed. Luckily an expert Amal Krishna Paul decided to contribute to this project. Then another problem arises which is the 'False Smut' is a seasonal disease and happens only at the very end when the rice is being plowed. So in order to collect the desired picture 6 long months had to be waited and finally during the end of November 2023 the time had arrived and with the help of an expert working the field the dataset was created. Another challenge we faced was during implementation of web application because when we ran the inceptionv3 model the tensorflow of that version was old compared to the tensorflow model that has been used during building the web application.

8.2 Future Work

One of the main motivations behind this project is to serve the people of the country and to do that the aim is to make a large application that can detect the disease of the plant provided by the user and also instruct them on what can be done to prevent the spreads of the disease. So far this project is just for one particular disease but the aim is to collect as many pictures of rice fungal-related diseases images across the country. So, eventually, it will be possible to help the farmers in rural areas where the necessary help is quite hard to get. Apply of the real-time video categorization capabilities to allow farmers to just point their smartphone cameras at their crops to obtain fast feedback on disease incidence and severity. This may be performed utilizing techniques like object detection and categorization in live video broadcasts.

Chapter 9

Conclusion

Deep learning techniques are the most effective solution for plant disease classification in recent time for image image processing and pattern recognition. This research will show the potential of image-processing techniques in the battle against fungal infections in rice plants, making a substantial contribution to the fusion of technology and agriculture. In order to lessen the catastrophic effects of fungal infections on rice harvests, the research offered a technology-driven solution that addressed a crucial issue in global food security. The CNN models outperformed the customized dataset having a higher accuracy with effective classification. In addition, data augmentation is a notable feature for the better efficiency of model training. The results of this study will not only provide a means of improving crop health but also serve as a model for future multidisciplinary projects aiming to revolutionize food production through cutting-edge technological innovations.

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