DETECTION OF PATHOGENS AFFECTING PADDY PLANTS AND A PREVENTATIVE METHOD BASED ON DEEP LEARNING

CO8811 – PROJECT REPORT

Submitted by

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in partial fulfillment for the award the degree

of

BACHELOR OF ENGINEERING

in

COMPUTER AND COMMUNICATION ENGINEERING

PANIMALAR ENGINEERING COLLEGE

(An Autonomous Institution, Affiliated to Anna University, Chennai)

MARCH 2024

BONAFIDE CERTIFICATE

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ACKNOWLEDGEMENT

We express our deep gratitude to our respected Secretary and Correspondent **Dr.P.CHINNADURAI, M.A., Ph.D.** for his kind words and enthusiastic motivation, which inspired us a lot in completing this project.

We would like to extend our heartfelt and sincere thanks to our Directors Tmt. **C.VIJAYARAJESWARI, Dr. C. SAKTHIKUMAR, M.E., Ph.D**., and **Dr.SARANYASREE SAKTHIKUMAR B.E., M.B.A., Ph.D**., for providing us with the necessary facilities for completion of this project.

We also express our gratitude to our Principal **Dr.K.MANI, M.E., Ph.D.,** for his timely concern and encouragement provided to us throughout the course.

We thank our HOD of Computer and Communication Engineering Department, **Dr. B. ANNI PRINCY, M.E., Ph.D**., Professor, for the support extended throughout the project.

We would like to thank our supervisor, **Mr. V. MUTHU, M.Tech., (Ph.D.)**., Associate Professor, and all the faculty members of the Department of Computer and Communication Engineering for their advice and suggestions for the successful completion of the project.

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ABSTRACT

Rice is the staple food for most of the tropical and subtropical countries of the world. This entails large fields of paddy spanning hectares, whose maintenance and care becomes a tedious task for the farmers. The caretakers aren't able to identify certain types of diseases and aren't able complete the tedious task of crop care in such a short span. Thus, motivated by this arduous exercise, this project suggests a solution for quick classification of paddy into diseased or healthy plants. If the plant is diseased, the area affected is identified. The image dataset used for this module is obtained from public platforms and consists of 3500 images of healthy and diseased paddy leaves. The classification module is created using deep learning network layers and provides accuracy of up to nearly 70%. This project reviews existing works on image classification using deep learning, introduces a new module for paddy disease classification and gives a reference for future work on the subject.

The efforts to increasing the quantity and quality of rice production are obstructed by the paddy disease. This research attempted to identify the major paddy diseases (leaf blast, brown spot and healthy) using fractal descriptors to analyses the texture of the lesions. The lesion images were extracted manually. The descriptors of `S' component of each lesion images then used in classification process using probabilistic neural networks.

Keywords: Paddy Disease Classification, Deep Learning, Image Classification, Rice Production, Identification of Diseases.

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S.NO	ABBREVATION	EXPANSION
1	ANN	Artificial Neural Network
2	DAE	Denoising Autoencoder
3	DNN	Deep Neural Network
4	DNN_JOA	Deep Neural Network Joint Optimization Algorithm
5	TP	True Positive
6	TN	True Negative
7	FP	False Positive
8	FN	False Negative

CHAPTER 1

INTRODUCTION

Rice diseases like brown spot cause major agricultural losses. Deep learning offers a powerful tool for early detection of these pathogens in paddy plants. By analyzing images, this approach can identify diseases with high accuracy, allowing for preventative measures and optimized resource use, potentially boosting rice yield and farmer profits.

1.1 GENERAL

Agriculture has always been a primary industry in any nation's economy. Various crops such as paddy, wheat, maize are grown in huge fields spanning hectares. Though factors like city expansion and urbanization are creating obstacles, the demand for agricultural products is more than ever. Technical aspects are being brought into the conventional art of farming to increase the produce multifold even when the land for farming remains the same. Hybrid seeds, Irrigation and crop care systems, and automated seed storage systems have been introduced to obtain and maintain large amounts of grains at a time. Technology is also being brought into different kinds of crop care systems to increase efficiency of care by attempting to reduce human error and loss.

The effect of climate change is evident in the growth of crops over time. Unseasonal rainfall and sunlight has resulted in improper growth of plants especially for paddy, where consistent weather conditions are required. Climate change also gives rise to improper land conditions which may hamper the growth of paddy or encourage growth of unnecessary weeds. Excessive rainfall also leads to depletion of nutrients through soil erosion. These climatic influences reduce the chances of crop sustenance and must be taken care of from the start of the cropping season.

The arrival of the Green Revolution in India brought along with many new industrial practices of agriculture. These include advanced practices of drip irrigation, tractors etc. The arrival of pesticides and fertilizers brought both positive and negative consequences. Even though they protected the plants from the pests, excessive dosage of these chemicals polluted the very soil which the crops use. Losses are also caused in biodiversity as nearby water resources are polluted. Thus it becomes necessary to find the pest infested areas along with the intensity to make most effective use of pesticides without damaging the crops.

1.2 PROBLEM STATEMENT

Rice, vital for billions, faces a constant threat from diverse diseases. Diagnosing the culprit behind outbreaks is slow and requires specialists, delaying action. This leads to ineffective, broad-spectrum chemicals that harm the environment. Additionally, farmers may overuse fertilizers to compensate for potential yield loss, causing further resource waste and environmental damage.

To safeguard rice production and food security, we urgently need a more precise approach to preventing paddy plant diseases. Rapid diagnostic tools that identify the specific pathogen are crucial. Imagine a simple, on-site kit allowing farmers to make informed treatment decisions. Early and precise diagnosis would enable targeted solutions, minimizing environmental impact.

Furthermore, promoting sustainable agriculture and integrated pest management (IPM) techniques can create a more resilient rice ecosystem. IPM focuses on preventative measures like crop rotation and balanced fertilization, fostering a healthy field environment less susceptible to disease.

The silent siege on rice demands action. Rapid diagnostics, coupled with sustainable practices, offer a path forward in safeguarding rice production and ensuring food security for future generations. By investing in these solutions, we can ensure this cornerstone crop continues to nourish billions for years to come.

1.3 OBJECTIVES

To detect pathogens affecting paddy plants using image analysis and deep learning techniques. To develop a deep learning-based system for early and accurate identification of paddy plant diseases. To propose preventative methods and solutions for managing the identified pathogens in paddy cultivation.

1.4 METHODOLOGY

Data Acquisition and Pre-processing

Data Collection gathers a dataset containing labeled images of healthy and diseased paddy plants. Sources include Public datasets (e.g., Kaggle)
Field-collected images with proper labeling (disease type)

Data Pre-processing formatting ensure consistent image format (size, resolution). Augmentation (Optional) increase dataset size and diversity Rotation, Flipping, Color jittering. Normalization Scale pixel values to a specific range (e.g., 0-1).

Data Splitting Divide the preprocessed data into three sets Training set Used to train the model (60-70% of data). Validation set Used to monitor model performance during training (10-15% of data). Testing set Used for final evaluation of the trained model (15-20% of data).

Model Development and Training

Model Selection choose the Mobile Net architecture due to its efficiency for mobile and embedded applications. Model Training define the model architecture (number of layers, filters, etc.) based on the dataset size and complexity. Train the model on the training set. The model learns to identify features in the images that distinguish between healthy and diseased leaves, potentially classifying different diseases based on the training data. Model Evaluation Evaluate the trained model's performance on the testing set. Use metrics like Accuracy Proportion of correctly classified images. Precision Ratio of true positives to all positive predictions. Recall Ratio of true positives to all actual positive cases. F1-score Harmonic mean of precision and recall.

Disease Detection and Prevention

Image Acquisition captures a new image of a paddy plant suspected of having a disease. Pre-processing apply the same pre-processing steps used on the training data to the new image. Prediction feed the pre-processed image into the trained Mobile Net model. The model predicts the presence and type of disease (based on training data) with a certain confidence level. Preventative Measures System suggests actions based on predicted disease Chemical control Fungicides, bactericides, or virucide. Cultural practices crop rotation, water management adjustments, or plant removal. Recommendations displayed or alerts sent to farmers/personnel.

1.5 LANGUAGE USED

Frontend (HTML/CSS)

HTML (Hyper Text Markup Language)**:** This is the foundation of web pages. It defines the structure and content of the web page, like headings, paragraphs, images, and buttons. HTML provides the basic building blocks for the user interface.

CSS (Cascading Style Sheets): CSS controls the visual presentation of the HTML content. It defines styles for elements like fonts, colors, layout, and positioning. CSS makes the web page visually appealing and user-friendly.

Backend (Flask/Python)

Flask This is a Python web framework that simplifies building web applications. It provides a flexible structure for handling user requests, routing them to appropriate functions, and generating responses. Flask takes care of the behind-the-scenes communication, allowing developers to focus on the program's core functionality.

Python (Domain) as discussed earlier, Python is the workhorse for the deep learning aspects. Libraries like Tensor Flow or PyTorch would be used within Flask to build and execute the deep learning model for pathogen detection in paddy plants. Python would also handle data processing tasks like loading and preparing images of paddy plants for the model.

CHAPTER 2

LITERATURE SURVEY

[1] **Title**: Rice disease classification based on leaf damage using deep learning.

Authors: Budi Dwi Satoto; Devie Rosa Anamisa; MohammadYusuf; Mohammad Kautsar Sophan; Nurwahyu Alamsyah

Year: 2022

Description: Rice is the staple food of the Indonesian people. Food security is an absolute thing to do today to reduce rice imports. Various efforts were made to improve seed quality, resistance to pests, nutrition, and so on. It helps to Analysis identify diseases that may arise in rice plants. Efforts were made using the image of leaves affected by the disease and then analyzed using a deep learning algorithm. The architecture used is google net and custom net. The selection is based on a good level of accuracy and the computational time required to obtainthe model. the convex hull algorithm helps to find the focus of disease objects on rice leaves. Data augmentation increases the variation in the amount of data and reduces unbalanced datasets. The results obtained are by using this algorithm, accuracy is obtained 80.94%, and the average computation time is three minutes and twenty seconds. Error calculation of classification are MSE 0.4227, RMSE 0.6501, and MAE 0.2555

[2] **Title**: Smartphone Application for Deep Learning-Based Rice Plant Disease Detection

Authors: Heri Andrianto; Suhardi; Ahmad Faizal; Fladio Armandika

Year: 2020

Description: An increase in the human population requires an increase in agricultural production. Generally, the most important thing in agriculture that affects the quantity and quality of crops is plant diseases. In general, a farmer knows that his plant is attacked by a disease through direct vision. However, this process is sometimes inaccurate. With the development of machine learning technology, plant disease detection can be done automatically using deep learning. In this study, we report on a deep learning-based rice disease detection system that we have developed, which consists of a machine learning application on a cloud server and an application on a smartphone. The smartphone application functions to capture images of rice plant leaves, send them to the application on the cloud server, and receive classification results in the form of information on the types of plant diseases. The results showed that the smartphone-based rice plant disease detection application functioned well, which was able to detect diseases in rice plants. The performance of the rice plant disease detection system with VGG16 architecture has a train accuracy value of 100% and a test accuracy value of 60%. The test accuracy value can be improved by adding the number of datasets and increasing the quality of the dataset. It is hoped that with this system, rice plant disease control can be carried out appropriately so that yields will be maximized.

[3] **Title**: Plant Disease Detection and Classification Using Deep Learning Model

Authors: Pushpa B R; Adarsh Ashok; Shree Hari A V

Year: 2021

Description: Organic farming is becoming more common in many developing countries agricultural practices. There are a variety of issues that occur in plant growth due to various environmental factors. Crop diseases can result in a reduction in agricultural productivity and hence identification of crop diseases in the beginning stage will provide great advantages towards the field of agriculture. In the recent years, Identification of leaf disease is done through image processingtechnique where feature extraction plays important part since using the right features leads to better classification accuracy. Nowadays, there exists lot of machine learning techniques to perform plant disease detection and identification, the advancement of deep learning gained attention due to improved performance and accuracy. So this paper presents a model for detecting and identifying crop leaf disease using CNN based Alex Net model. This proposed model is compared with other CNN model (VGG-16 and Lenet-5) that shows our proposed Alex Net model is more accurate than VGG-16 and Lenet-5. The dataset considered for experimentations are collected from plant village repository with total number of 7070 diseased and healthy leaf images of corn blight, Corn Common Rust, Corn Gray Leaf Spot, Rice Bacterial leaf blight, Rice Brown spot, Rice Leaf smut, Tomato Bacterial spot, Tomato Early blight, Tomato Target Spot and Tomato mosaic virus. The proposed method will successfully identify the crop species with 96.76 % accuracy.

[4] **TITLE**: Deep Learning Analysis of Rice Blast Disease Using RemoteSensing Images

Authors: Shubhajyoti Das, Arindam Biswas, Vimalkumar c.

Year: 2023

Description: Real-time disease monitoring in large-scale farming, like for rice, is vital. Remote sensing, with spectral indices, distinguishes healthy and infected crops efficiently. Deep learning achieves 90.02% training and 85.33% validation accuracy, enabling real-time leaf blast assessment. This aids proactive measures, resource optimization, and better food security. Large farms, like rice paddies, need constant vigilance against disease. Thankfully, remote sensing technology offers a powerful solution. By analyzing the unique light reflected by healthy and infected plants (spectral indices), this approach efficiently identifies problem areas. Deep learning algorithms further enhance this by achieving high accuracy in disease detection, like rice blast. This real-time data allows farmers to take proactive steps, optimize resources, and ultimately contribute to a more secure food supply. Satellite tech spots sick crops in real-time. Deep learning analyzes light patterns for 85% disease accuracy. Farmers fight illness faster, boosting food security.

[5] **Title**: Automated Recognition of Rice Grain Diseases Using Deep Learning

Authors: Solayman Hossain Emon; MD Afranul Haque Mridha; Mohtasim Shovon

Year: 2020

Description: To detect and classify various diseases of plants, the images of leaves are the main wellspring of information. Misidentifying various diseases in agricultural crops can lead to significant economic loss and environmental impacts. Rice is the most predominant food crop in Bangladesh. It possesses around 75% of the grossed harvest area of the country. Early diagnosis of rice grain diseases can save tones of agricultural products every year. The traditional manual observation of the crop disease is time-consuming and less accurate. For addressing this issue, researchers have utilized different high-performing Convolutional Neural Networks (CNNs) that perform well in the disease classification tasks. But these networks have very complex architecture and not very much suitable for real-life applications. Moreover, there is a limitation of devices and stable connectivity in agricultural areas. So there requires a lightweight efficiency for applying the automated disease detection system. In this paper, we present a custom memory-efficient Convolutional Neural Network (CNN) namely, Rice Net to automatically detect rice grain diseases. An extensive experiment showed the effectiveness of the proposed custom network (Rice Net) which provides a classification accuracy of 93.75%. We also apply the transfer learning approach through various pre-trained lightweight structures and achieved 97.94% accuracy through EfficientNetB0.

[6] **Title**: A Review on Machine Learning Classification Techniques forPlant Disease Detection

Authors: U. Shruthi; V. Nagaveni; B.K. Raghavendra

Year: 2019

Description: In India, Agriculture plays an essential role because of the rapid growth of population and increased in demand for food. Therefore, it needs to increase in crop yield. One major effect on low crop yield is disease caused by bacteria, virus and fungus. It can be prevented by using plant diseases detection techniques. Machine learning methods can be used for diseases identification because it mainly applies on data themselves and gives priority to outcomes of certain task. This paper presents the stages of general plant diseases detection system and comparative study on machine learning classification techniques for plant disease detection. In this survey it observed that Convolutional Neural Network gives high accuracy and detects more number of diseases of multiple crops.

[7] **Title**: Rice Leaf Diseases Classification Using CNN with Transfer Learning

Authors: Shreya Ghosal; Kamal Sarkar

Year: 2022

Description: Rice is one of the major cultivated crops in India which is affected by various diseases at various stages of its cultivation. It is very difficult for the farmers to manually identify these diseases accurately with their limited knowledge. Recent developments in Deep Learning show that Automatic Image Recognition systems using Convolutional Neural Network (CNN) models can be very beneficial in such problems. Since rice leaf disease image dataset is not easily available, we have created our own dataset which is small in size hence we have used Transfer Learning to develop our deep learning model. The proposed CNN architecture is based on VGG-16 and is trained and tested on the dataset collected from rice fields and the internet. The accuracy of the proposed model is92.46%.

[8] **Title:** Application of Pre-Trained Deep Convolutional Neural Networks forRice Plant Disease Classification

Authors: Vimal K. Shrivastava; Monoj K. Pradhan; Mahesh P. Thakur

Year: 2021

Description: Rice is a primary food and encounters an essential role in providingfood security worldwide. However, several diseases affect this crop that significantly reduces its production and quality. Therefore, early detection of diseases is much needed task to prevent spreading of diseases. Hence, it is desirable to develop an automatic system which will help agronomist, pathologist and even the farmers to diagnose the rice diseases more efficiently and take preventive measures in time. In the present era of advanced artificial intelligence, various learning techniques have been explored for rice plant disease classification. Among various machine learning techniques, deep learning has been widely applied in various domains of computer vision and image analysis recently. It has successfully delivered promising results with large potential. However, training the deep learning model from the scratch requires huge labeled data and collection of huge labeled data is expensive, laborious and time taking process. Transfer learning of pre-trained deep learning model is a technique to overcome such problems. This paper has explored the performance of various pre-trained deep CNN models such as: (i) Alex Net; (ii) Vgg16; (iii) ResNet152V2; (iv) InceptionV3; (V) InceptionResNetV2; (vi) Exception; (vii) Mobile Net; (viii) DenseNet169; (ix) NasNetMobile; and (x) NasNetLarge for image based rice plant disease classification. The dataset used in this paper consist of 1216 rice plant diseased images and these have been collected from thereal agricultural field having seven classes: (i) rice blast; (ii) bacterial leaf blight;(iii) brown spot; (iv) sheath blight; (v) sheath rot; (vi) false smut; (vii) healthy leaves. The Vgg16 model resulted highest classification accuracy of 93.11%. The outcome of the model can be used as an advisory and as an early detection tool inthe real agriculture domain.

[9] **Title:** Deep Learning-based Identification and Classification of Rice Plant Diseases for Precision Agriculture

Authors: N. Venkatesh; Swagata Sarkar; A Sunil; T.Guru Priya; R Aarthi; K.Mekala Devi

Year: 2023

Description: Because they reduce both the quality and yield of crops, plant diseases seriously threaten our food supply's reliability. Plant diseases often result in a significant reduction or complete absence of grain yield in various agricultural contexts. Classifying rice plant diseases and insects pose a significant challenge due to the intricate structure of their composition and the striking resemblance 5bserved among various disease types and insect species. Diseases and insects in crops must be discovered and categorized as soon as possible, ideally before they may spread. There are a number of methods for spotting plant diseases, but deep learning is now the gold standard. The authors provide a novel deep-learning approach for detecting diseases in rice fields using photographs. Convolutional Neural Networks with attention mechanism (CNNAM) can be used to detect diseases in rice plants. Due to its reliability in picture identification and classification, CNNs have been widely employed by researchers for plant disease identification. The identification of rice plant diseases, however, has only been the subject of a small number of studies. This research illuminates the present state of rice plant disease and the methods of disease detection based on Deep Learning. Deep learning models excel about more conventional machine learning methods. With the suggested model, authors were able to categorize rice photos with a 99.8 percent accuracy by learning latent patterns in the raw images.

[10] **Title:** Disease Classification in Paddy Crop Leaves Using Deep Learning

Authors: S Kavin Kumar; T Kowshik; M Krishna Harini; R. Kingsy Grace

Year: 2023

Description: Rice, a staple food for billions, faces a constant threat – diseases that can devastate yields. Traditionally, farmers rely on visual inspection to identify these threats, a method that is both slow and prone to error. However, a new study proposes a game-changer: a machine learning system for accurate and efficient paddy disease detection using image analysis. This innovative system empowers farmers by allowing them to simply capture pictures of their rice plants. The system, trained on a meticulously curated library of images depicting healthy and diseased plants, then analyses the captured image for crucial details. Colour variations, textural patterns, and even the shape of the leaves are meticulously scrutinized. The magic lies in a powerful algorithm called a Convolutional Neural Network (CNN). This sophisticated tool analyses the visual data, acting like a digital plant doctor. With an impressive 89% accuracy, the CNN can effectively distinguish healthy plants from their disease-ridden counterparts.

CHAPTER 3

SYSTEM DEVELOPMENT

3.1 FEASIBILITY STUDY

A feasibility study suggests promise for developing a deep learning system to detect pathogens in paddy plants and recommend preventative actions. Deep learning has shown success in plant disease detection, offering the technical foundation for this project. The economic benefits are substantial, potentially leading to reduced crop loss, targeted pesticide use, and improved crop quality. Challenges exist in acquiring a large, diverse dataset of paddy plant images with various pathogens and ensuring user-friendliness for farmers, particularly in areas with limited internet connectivity. However, a pilot project can assess technical performance and user acceptance, paving the way for a potentially transformative tool for the agricultural industry.

However, challenges exist. Acquiring a large and diverse dataset of paddy plant images featuring various pathogens is crucial. Additionally, ensuring user-friendliness for farmers, especially in areas with limited internet connectivity, is paramount.

Despite these hurdles, a pilot project can be instrumental. By assessing both technical performance and user acceptance, it can pave the way for a truly transformative tool for the agricultural industry. This system has the potential to revolutionize rice production by empowering farmers with a powerful disease detection and prevention solution.

3.2 MODEL DEVELOPMENT

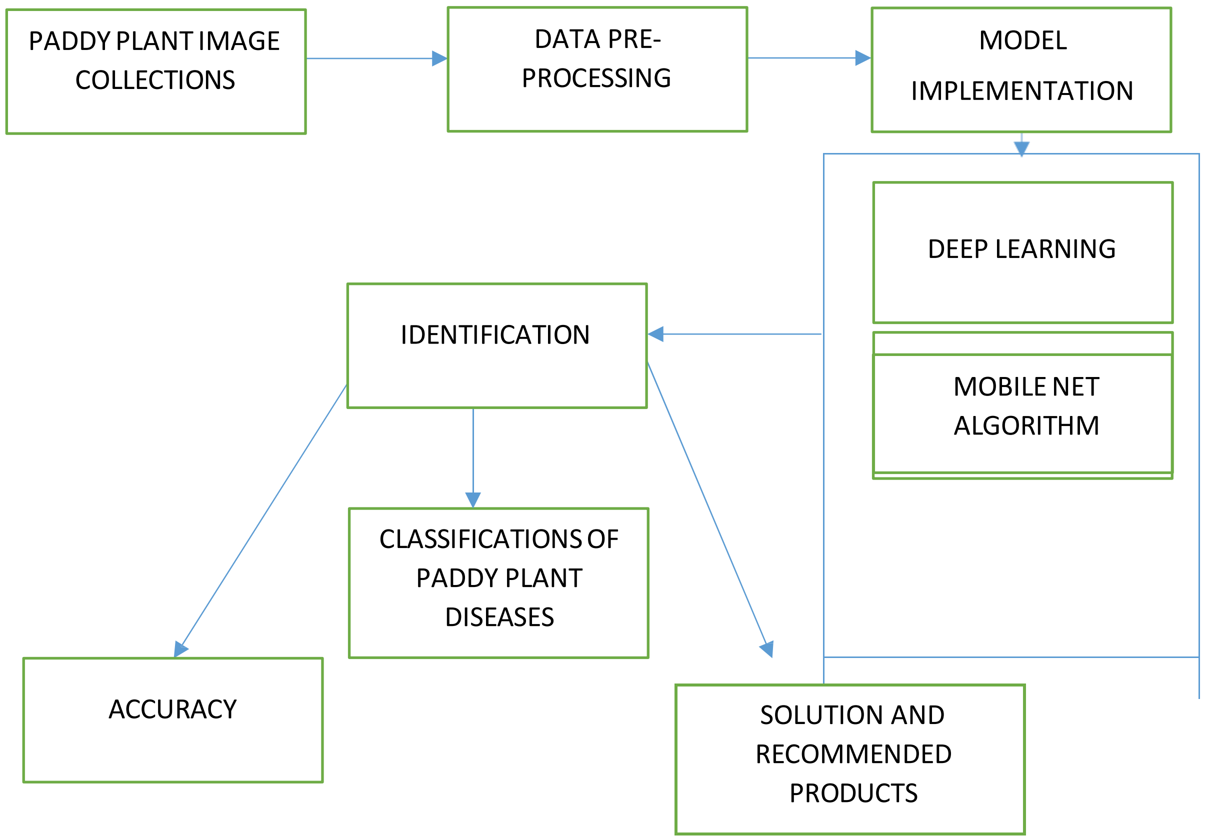


Figure 3.1 Block Diagram Of Proposed System

The process begins Figure 3.1 with collecting diverse and high-quality images of paddy plants, which are then pre-processed to remove noise and enhance image quality. These images are split into training and testing sets for deep learning model implementation, with the MobileNet algorithm often used for its efficiency. The trained model identifies disease patterns in paddy plant images, which are then classified to understand disease types accurately. Accuracy evaluation against standards ensures reliable results. Finally, actionable recommendations are provided based on disease classifications, including disease-specific treatments, integrated pest management strategies, early detection and monitoring, soil health management, educational outreach, continuous monitoring, access to resources, and stakeholder collaboration. These recommendations aim to ensure healthy crop yields and sustainable agricultural practices in paddy farming.

3.3 Description of each block

Data collection

Data collection is the initial phase of gathering relevant information or observations to support a particular objective or analysis. In the context of paddy plant disease identification and management, data collection involves acquiring various types of data related to paddy plants, including images, environmental factors, disease symptoms, and historical records. This data serves as the foundation for subsequent analysis, model training, and decision-making processes. Key aspects of data collection in this context may include:

Image Collection: Gathering a diverse set of images depicting paddy plants at different growth stages and under various environmental conditions. These images should cover healthy plants as well as those affected by different diseases to train the model effectively.

Environmental Data: Recording environmental factors such as temperature, humidity, rainfall, and soil conditions that can influence the incidence and severity of paddy plant diseases. This data helps in understanding disease dynamics and predicting disease outbreaks.

Disease Symptoms: Documenting the visual symptoms and patterns associated with different paddy plant diseases, including leaf lesions, discoloration, wilting, and deformities. Accurate symptom documentation aids in disease identification and classification.

Geospatial Information: Capturing geospatial data such as GPS coordinates or field locations where paddy plants are cultivated. Geospatial information enables spatial analysis and mapping of disease prevalence and distribution patterns.

Historical Records: Collecting historical data on past disease outbreaks, crop management practices, pest infestations, and yield fluctuations. Historical records provide valuable insights into recurring patterns and trends, helping to inform decision-making and preventive measures.

Data Annotation and Labeling: Annotating and labeling collected data to indicate the presence of diseases or other relevant features in images. Proper annotation facilitates supervised learning approaches and model training for disease identification.

Quality Assurance: Ensuring the quality and reliability of collected data through rigorous validation, verification, and data cleaning processes. This involves checking for errors, inconsistencies, or biases in the collected data to maintain data integrity.

Ethical Considerations: Adhering to ethical guidelines and obtaining necessary permissions or consents for data collection, especially when involving human subjects or sensitive information. Respecting privacy rights and ensuring data confidentiality are essential considerations.

Effective data collection lays the groundwork for subsequent analysis, model development, and decision support in paddy plant disease management. It is crucial to employ systematic approaches, utilize appropriate tools and technologies, and adhere to ethical standards throughout the data collection process.

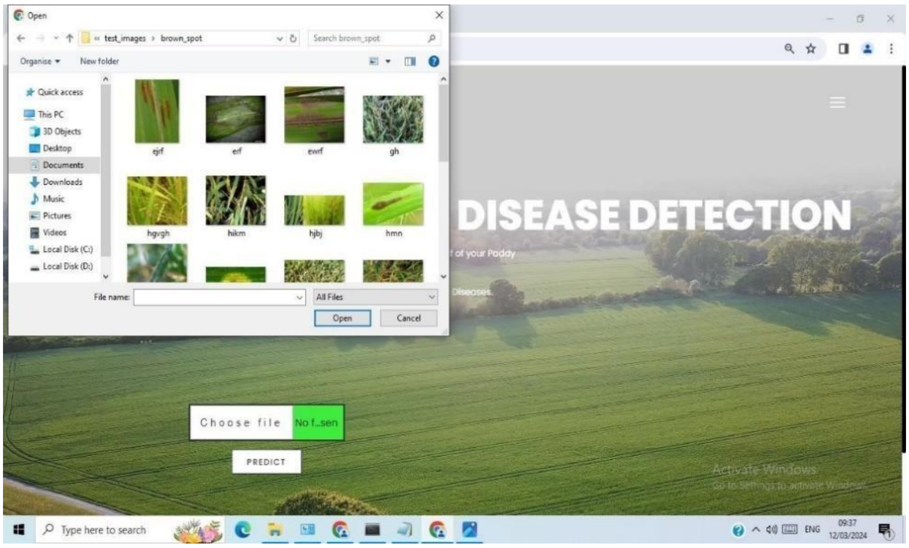


Figure 3.2 Data Collection Images.

Data Pre-Processing

Data pre-processing is a critical step in preparing collected data for further analysis, model training, and decision-making processes. In the context of paddy plant disease identification and management, data pre-processing involves several key tasks aimed at cleaning, organizing, and formatting the data to ensure its quality and suitability for subsequent analysis. Here are the main aspects of data pre-processing:

Noise Removal: Eliminating irrelevant or extraneous information from the collected data, such as artifacts, background noise, or irrelevant features in images. This can involve techniques such as image denoising, background subtraction, or filtering to enhance the signal-to-noise ratio and improve data quality.

Image Enhancement: Enhancing the visual quality and clarity of collected images to facilitate accurate analysis and disease identification. Image enhancement techniques may include contrast adjustment, brightness normalization, color correction, and sharpening to improve image quality and highlight relevant features.

Data Formatting: Standardizing the format and structure of collected data to ensure consistency and compatibility across different datasets and analysis tools. This may involve converting data into a common file format (e.g., CSV, JSON, HDF5) and organizing it into a structured hierarchy or database for efficient storage and retrieval.

Normalization and Scaling: Scaling numerical data to a standardized range or distribution to improve model performance and convergence during training. This can involve techniques such as feature scaling, min-max scaling, or z-score normalization to ensure that all input variables have similar scales and ranges.

Data Augmentation: Increasing the diversity and size of the dataset by generating synthetic data samples through techniques such as image rotation, flipping, cropping, or adding noise. Data augmentation helps prevent overfitting, improves model generalization, and enhances the robustness of trained models to variations in input data.

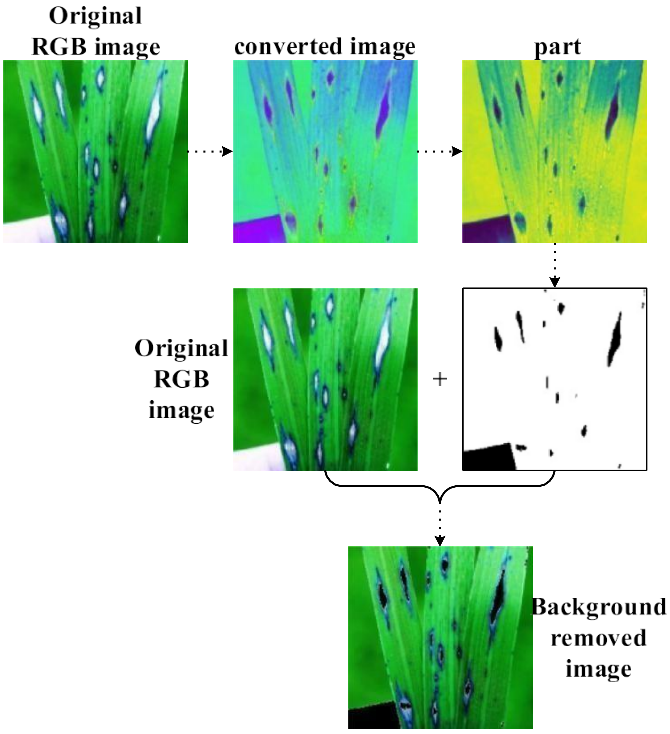


Figure 3.3 Image Pre-Processing**.**

Missing Data Handling: Addressing missing or incomplete data points in the dataset by imputation or deletion. Depending on the extent of missing data and the nature of the analysis, missing data may be imputed using techniques such as mean imputation, median imputation, or regression imputation, or data samples with missing values may be removed.

Feature Selection and Extraction: Identifying and selecting the most relevant features or variables from the dataset that contribute most to the predictive task or analysis objectives. Feature selection techniques such as correlation analysis, mutual information, or principal component analysis (PCA) can be used to reduce dimensionality and focus on informative features.

Quality Control: Conducting quality control checks and validation procedures to ensure the integrity, accuracy, and reliability of pre-processed data. This involves identifying and addressing outliers, errors, or anomalies in the data and verifying data consistency and correctness through manual inspection or automated validation checks.

By performing these data pre-processing tasks effectively, researchers and practitioners can ensure that the collected data is clean, standardized, and well-prepared for subsequent analysis, model training, and decision support in paddy plant disease management. This enhances the accuracy, reliability, and effectiveness of data-driven approaches in addressing agricultural challenges and optimizing crop health and productivity.

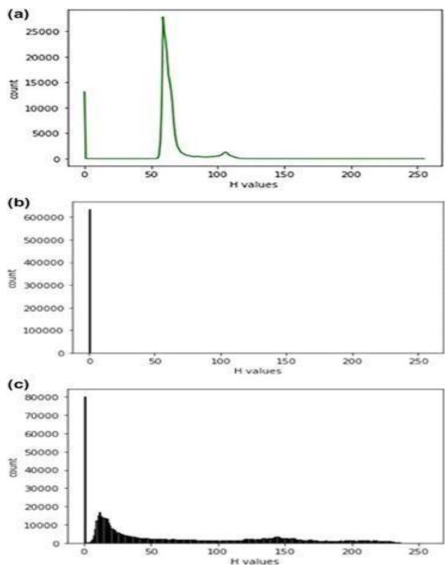


Figure3.4 Processing Graph Analysis.

Model Implementation

Model Implementation in the realm of deep learning involves a systematic process aimed at harnessing the predictive power of algorithms to solve specific tasks, such as predicting . The journey begins with data collection, where a comprehensive dataset is amassed containing relevant

Once collected, the data undergoes a transformation akin to preparing ingredients for a recipe. This involves cleaning the data to remove errors and inconsistencies and preprocessing it to format numbers and handle missing values effectively. The dataset is then divided into two essential subsets: the training set, which forms the basis for model learning, and the testing set, which evaluates the model's performance.

Choosing the right algorithm is paramount. For instance, MobileNet, a type of convolutional neural network (CNN), excels in tasks with constraints on computational resources, such as mobile applications. Its specialized architecture achieves high accuracy with minimal computational needs, making it suitable for real-world deployment.

A deep learning model can be a useful tool for paddy plant disease identification and prevention. It functions as follows: A convolutional neural network (CNN) is trained using a dataset of photographs displaying both healthy and unhealthy paddy leaves. By studying these images, the CNN learns to identify patterns linked to specific diseases. Following training, the model is able to recognize potential epidemics, determine the kind and severity of sickness, and assess recently taken images of paddy leaves. Then, armed with this information, preventative actions can be carried out, such as recommending appropriate fungicides or insecticides in accordance with the identified disease. This method's ability to identify diseases early leads to increased agricultural output and more targeted resource management.

During the training phase, the algorithm processes the training set, identifying intricate patterns and relationships within the data. This learning process is fundamental to deep learning, enabling algorithms to glean insights from vast datasets that traditional programming methods struggle to handle.

Following training, the model's proficiency is evaluated using the untouched testing set, gauging its ability to generalize knowledge to unseen data—a critical step in ensuring real-world effectiveness.

With a well-trained and validated model, predictive capabilities are unlocked. In the case of house price prediction, the model can make educated guesses about the value of new properties based on learned relationships between various factors.

However, successful model implementation hinges on several factors. Adequate data availability and relevance are crucial, as deep learning models require substantial datasets for effective training. Moreover, computational resources, such as powerful computers or GPUs, may be necessary due to the computational intensity of training deep learning models.

Choosing the appropriate algorithm is equally vital, with considerations for task-specific requirements and data characteristics. While MobileNet may suit mobile applications, other algorithms might better serve different tasks or datasets.

In essence, model implementation involves a meticulous process of collecting and preparing data, selecting the right algorithm, training and evaluating the model, and ultimately leveraging its predictive power. It's not magic but the culmination of sophisticated algorithms learning from vast datasets, paving the way for intelligent predictions.

IDENTIFICATION

Predicting paddy plant diseases with deep learning follows a fascinating journey. It starts with gathering a vast collection of images show casing healthy and diseased plants. These images undergo some prep work, like resizing and labeling them based on the specific disease. Next, the data gets split into two groups: training and testing. The training set acts as the teacher, guiding the deep learning algorithm, in this case Mobile Net. Mobile Net, known for its efficiency, is a type of algorithm adept at image recognition. As Mobile Net processes the training images, it uncovers hidden patterns that differentiate healthy from diseased plants, and even identify specific diseases. Finally, the testing set puts the trained model to the test. If successful, this model can then analyse figure 3.4 entirely new images, classifying them based on the diseases it learned from the training data. However, keep in mind that deep learning thrives on large datasets, so the more images the model trains on, the better.

3.4 DATA SET USED IN THE PADDY PLANT DISEASES

These paddy plant disease detection datasets are often open-source, meaning anyone can access this valuable resource. This fuels collaboration between researchers and developers, accelerating advancements in deep learning for agriculture

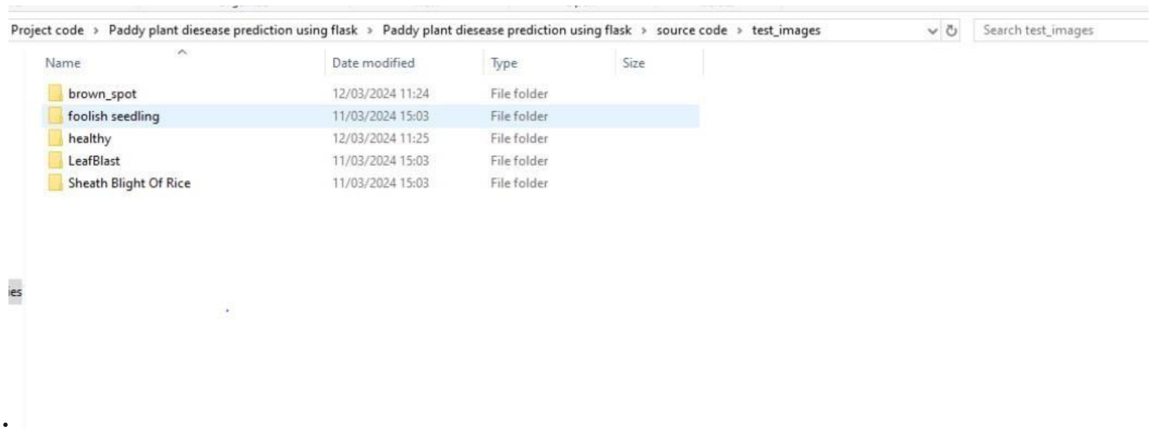


Figure3.5 Data Storage Space.

Figure 3.6: Example Of Paddy Plant Diseases**.**

3.5 ALGORITHM

MOBILE NET ALGORITHM

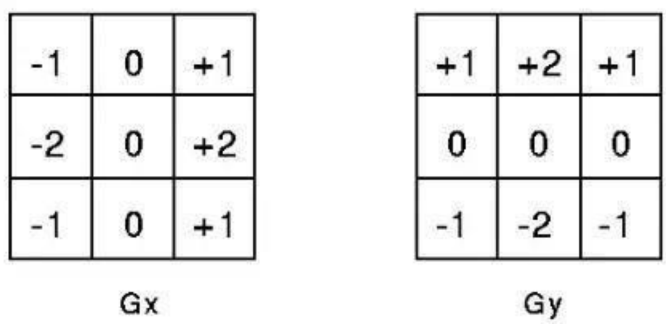
As the name applied, the Mobile Net model is designed to be used in mobile applications, and it is Tensor Flow’s first mobile computer vision model. Mobile Net uses depth wise separable convolutions. It significantly reduces the number of parameters when compared to the network with regular convolutions with the same depth in the nets. This results in lightweight deep neural networks.

A depth wise separable convolution is made from two operations. Depth wise convolution. Point wise convolution.

Mobile Net is a class of CNN that was open-sourced by Google, and therefore, this gives us an excellent starting point for training our classifiers that are insanely small and insanely fast.

Depth wise Separable Convolution

This convolution originated from the idea that a filter’s depth and spatial dimension can be separated- thus, the name separable. Let us take the example of Sobel filter, used in image processing to detect edges.



-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Figure 3.7 Depth wise Separable Convolution

The figure3.7 shows two 3x3 grids, which represent the kernels used in the Sobel operator for calculating the image gradients in horizontal (Gx) and vertical (Gy) directions.You can separate the height and width dimensions of these filters. Gx filter can beviewed as a matrix product of [1 2 1] transpose with [-1 0 1].

We notice that the filter had disguised itself. It shows it had nine parameters, but it has 6. This has been possible because of the separation of its height and width dimensions.

The same idea applied to separate depth dimension from horizontal (width*height) gives us depth-wise separable convolution where we perform depth-wise convolution. After that, we use a 1*1 filter to cover the depth dimension.

Standard convolution analyzes images with a single filter, like a big net scooping everything at once. Depth-wise separable convolution works smarter. It separates image data: width, height (spatial) and different features (channels).The first step, depth-wise convolution, acts like many specialized sieves. Each sieve focuses on a single channel, sifting out spatial details specific to that feature. Imagine having separate sieves for different types of grain, sorting them by size. Finally, a tiny 1x1 filter combines everything. This "chef" filter mixes the features from each channel (like mixing sorted grains) to create the final output. The key is efficiency. Depth-wise separable convolution uses smaller filters, reducing computational cost. Yet, the tiny filter still allows combining information for complex features. This makes it ideal for lighter models or situations with limited resources.

This efficiency lies in the use of smaller filters. Depth-wise separable convolution significantly reduces computational cost by employing these filters. Remarkably, the tiny 1x1 filter in the final step still allows for the combination of information from each channel, enabling the model to capture complex features. This makes depth-wise separable convolution particularly well-suited for scenarios where lighter models are preferred, or where computational resources are limited.

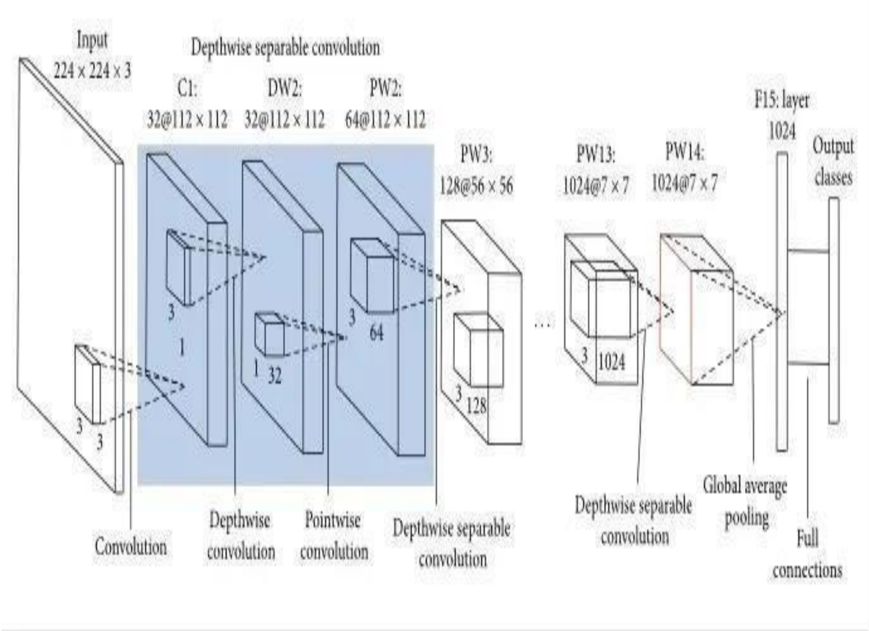


Figure 3.8: Mobile Net architecture.

Flow Diagram Of Mobile Net Architecture

This flowchart serves as a roadmap for managing pathogens in your paddy fields using deep learning. The process begins with identifying the culprit – the specific pathogen harming your crops. Deep learning steps in to analyze data, potentially using image recognition or other techniques, to pinpoint the exact pathogen type. Armed with this knowledge, the flowchart recommends suitable prevention methods tailored to the specific pathogen and the severity of the infestation. But the journey doesn't end there. The flowchart emphasizes the importance of monitoring your paddy's health to assess the effectiveness of the chosen method. If the monitoring reveals issues, the flowchart allows for adjustments to the prevention strategy, ensuring you have the best chance of keeping your paddy crops healthy.

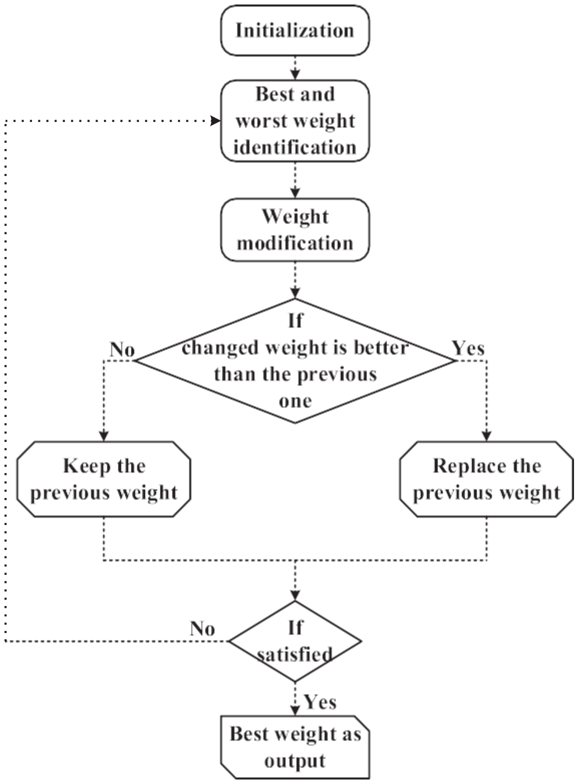


Figure 3.9 Flow Diagram of Algorithm

Deep Learning Diagnosis

The process starts by capturing images of the affected paddy crop. These images are then fed into a deep learning model specifically trained to identify different types of paddy pathogens. This model analyzes the visual signs of damage and outputs the most likely culprit, providing a crucial first step in combating the issue.

Severity Assessment

Just identifying the pathogen isn't enough. This step involves assessing the severity of the infestation. It might go beyond the captured images and consider factors like the overall extent of damage observed in the paddy field or additional data collected from the field (e.g., temperature, humidity). This assessment helps determine the appropriate course of action.

Tailored Management Options

Based on the deep learning diagnosis and the severity assessment , the program recommends suitable management options. This ensures targeted solutions – the program suggests methods specifically effective against the identified pathogen and the level of infestation it presents.

Implementation and Monitoring

Here's where action is taken! The grower selects the most appropriate management option from the recommendations, considering factors like resource availability and regulations. Once implemented (e.g., applying fungicides, introducing beneficial insects), the paddy's health is closely monitored. This monitoring is crucial to assess the effectiveness of the chosen method and identify any need for adjustments.

Adaptive Management

The final point emphasizes the adaptability of the process. The monitoring in might reveal that the chosen management option isn't effectively controlling the pathogen. In such cases, the program allows for adjustments. The grower might need to revisit the recommendations based on the updated information or refine the implementation of the current method. This ensures a dynamic approach that adapts to the specific circumstances of the paddy field.

CHAPTER 4

TESTING AND REQUIREMENT SPECIFICATION

4.1 TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub – assemblies, assemblies and/or a finished product It is the process of exercising software with the intent of ensuring that the system.

Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

TYPES OF TESTS

UNIT TESTING

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

INTEGRATION TESTING

Integration tests are designed to test integrated software components to determine if they actually run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfaction, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

FUNCTIONAL TEST

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items

Valid Input: identified classes of valid input must be accepted.

Invalid Input: identified classes of invalid input must be rejected.

Functions: identified functions must be exercised.

Output: identified classes of application outputs must be exercised

Procedures: interfacing systems or procedures must be invoked.

Organization and preparation of functional tests is focused on requirements, key functions, or special test cases. In addition, systematic coverage pertaining to identify Business process flows; data fields, predefined processes, and successive processes must be considered for testing. Before functional testing is complete, additional tests are identified and the effective value of current tests is determined.

SYSTEM TEST

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

WHITE BOX TESTING

White Box Testing is a testing in which in which the software tester has knowledge of the inner workings, structure and language of the software, or at least its purpose. It is purpose. It is used to test areas that cannot be reached from a black box level.

BLACK BOX TESTING

Black Box Testing is testing the software without any knowledge of the inner workings, structure or language of the module being tested. Black box tests, as most other kinds of tests, must be written from a definitive source document, such as specification or requirements document, such as specification or requirements document. It is a testing in which the software under test is treated, as a black box. You cannot ―see‖ into it. The test provides inputs and responds to outputs without considering how the software works.

UNIT TESTING

Unit testing is usually conducted as part of a combined code and unit test phase of the software lifecycle, although it is not uncommon for coding and unit testing to be conducted as two distinct phases.

Test strategy and approach

Field testing will be performed manually and functional tests will be written in detail.

Test objectives. All field entries must work properly. Pages must be activated from the identified link.The entry screen, messages and responses must not be delayed. integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

4.2 REQUIREMENT SPECIFICATION

Requirements are a feature of a system or description of something that the system is capable of doing in order to fulfil the system’s purpose. It provides the appropriate mechanism for understanding what the customer wants, analyzing the needs assessing feasibility, negotiating a reasonable solution, specifying the solution unambiguously, validating the specification and managing the requirements as they are translated into an operational system.

PYTHON

Python is a dynamic, high level, free open source and interpreted programming language. It supports object-oriented programming as well as procedural oriented programming. In Python, we don’t need to declare the type of variable because it is a dynamically typed language. For example, x=10. Here, x can be anything such as String, int, etc. Python is an interpreted, object-oriented programming language similar to PERL, that has gained popularity because of its clear syntax and readability. Python is said to be relatively easy to learn and portable, meaning its statements can be interpreted in a number of operating systems, including UNIX-based systems, Mac OS, MS-DOS, OS/2, and various versions of Microsoft Windows 98. Python was created by Guido van Rossum, a former resident of the Netherlands, whose favourite comedy group at the time was Monty Python's Flying Circus. The source code is freely available and open for modification and reuse. Python has a significant number of users.

Features in Python

There are many features in Python, some of which are discussed below

- Easy to code
- Free and Open Source
- Object-Oriented Language
- GUI Programming Support
- High-Level Language

- Extensible feature
- Python is Portable language
- Python is Integrated language
- Interpreted Language

ANACONDA

Anaconda distribution comes with over 250 packages automatically installed, and over 7,500 additional open-source packages can be installed from PYPI as well as the Anaconda package and virtual environment manager. It also includes a GUI, Anaconda Navigator, as a graphical alternative to the command line interface (CLI). The big difference between Anaconda and the package manager is in how package dependencies are managed, which is a significant challenge for Python data science and the reason Anaconda exists. When pip installs a package, it automatically installs any dependent Python packages without checking if these conflict with previously installed packages. It will install a package and any of its dependencies regardless of the state of the existing installation. Because of this, a user with a working installation of, for example, Google Tensor flow, can find that it stops working having used pip to install a different package that requires a different version of the dependent numpy library than the one used by Tensor flow. In some cases, the package may appear to work but produce different results in detail. In contrast, Anaconda analyses the current environment including everything currently installed, and, together with any version limitations specified (e.g., the user may wish to have Tensor flow version 2,0 or higher), works out how to install a compatible set of dependencies, and shows a warning if this cannot be done. Open source packages can be individually installed from the Anaconda repository, Anaconda Cloud (anaconda.org), or the user's own private repository or mirror, using the Anaconda install command. Anaconda, Inc. compiles and builds the packages available in the Anaconda repository itself, and provides binaries for Windows 32/64 bit, Linux 64 bit and Mac OS 64-bit. Anything available on PyPI may be installed into a Anaconda environment using pip, and Anaconda will keep track of what it has installed itself and what pip has installed. Custom packages can be made using the Anaconda build command, and can be shared with others by uploading them to Anaconda Cloud, PyPI or other repositories. The default installation of Anaconda2 includes Python 2.7 and Anaconda3 includes Python 3.7. However, it is possible to create new environments that include any version of Python packaged with Anaconda.

ANACONDA NAVIGATOR

Anaconda Navigator is a desktop graphical user interface (GUI) included in Anaconda distribution that allows users to launch applications and manage Anaconda packages, environments and channels without using command-line commands. Navigator can search for packages on Anaconda Cloud or in a local Anaconda Repository, install them in an environment, run the packages and update them. It is available for Windows, MacOS and Linux.

The following applications are available by default in Navigator: [16]

- Jupyter lab
- Jupyter Notebook
- Qt Console
- Spyder
- Glue
- Orange
- R Studio
- Visual Studio Code

JUPYTER NOTEBOOK

Jupyter Notebook (formerly IPython Notebooks) is a web-based interactive computational environment for creating Jupiter notebook documents. The "notebook" term can colloquially make reference to many different entities, mainly the Jupiter web application, Jupiter Python web server, or Jupyter document format depending on context. A Jupiter Notebook document isa JSON document, following a versioned schema, containing an ordered list of input/output cells which can contain code, text (using Markdown), mathematics, plots and rich media, usually ending with the ".ipynb" extension.

Jupyter Notebook can connect to many kernels to allow programming in different languages.

By default, Jupiter Notebook ships with the I Python kernel. As of the release[11][12] (October 2014), there are currently 49 Jupyter-compatible kernels for many programming languages, including Python, R, Julia and Haskell.

The Notebook interface was added to IPython in the 0.12 release[14] (December 2011), renamed to Jupiter notebook in 2015 (IPython 4.0 – Jupyter 1.0). Jupiter Notebook is similar to the notebook interface of other programs such as Maple, Mathematica, and Sage Math , a computational interface style that originated with Mathematica in the 1980s. According to The Atlantic, Jupiter interest overtook the popularity of the Mathematica notebook interface in early 2018.

RESOURCE REQUIREMENTS

Operating System	Windows 7 or later
Simulation Tool	Anaconda (Jupiter notebook)
Documentation	Ms – Office

Table 4.1 Table Of SOFTWARE REQUIREMENTS

Anaconda with Jupyter Notebook offers a powerful environment for Python coding and data visualization. Jupyter Notebooks allow you to write code, analyze data, and see the results interactively.

CPU type	I5
Ram size	4GB
Hard disk capacity	80 GB
Keyboard type	Internet keyboard
Monitor type	15 Inch colour monitor
CD -drive type	52xmax

Table 4.2 Table Of HARDWARE REQUIREMENTS

This system utilizes an i5 processor with 4GB of RAM for efficient data handling. Storage is provided by an 80GB hard drive. A standard internet keyboard allows for data input, while a 15-inch color monitor displays information. For media loading, a 52x maximum speed CD-ROM drive is included.

CHAPTER 5

PERFORMANCE ANALYSIS

Deep learning tackles paddy plant disease detection, but its effectiveness needs evaluation. Metrics like accuracy, precision, and recall assess how well the model classifies healthy vs. diseased plants. Confusion matrices and ROC curves further analyze these classifications. Data quality, model architecture, and training parameters all affect performance. Analyzing weaknesses allows targeted improvements for healthier crops and increased food security.

ACCURACY

Accuracy is a commonly used metric to evaluate the performance of a classification model. It represents the proportion of correctly classified instances (both positive and negative) among all instances in the dataset.

Accuracy = (True Positives + True Negatives) / (Total Images) ×100%

True Positives (TP): Images correctly classified as diseased. **True Negatives (TN)**:Images correctly classified as healthy.

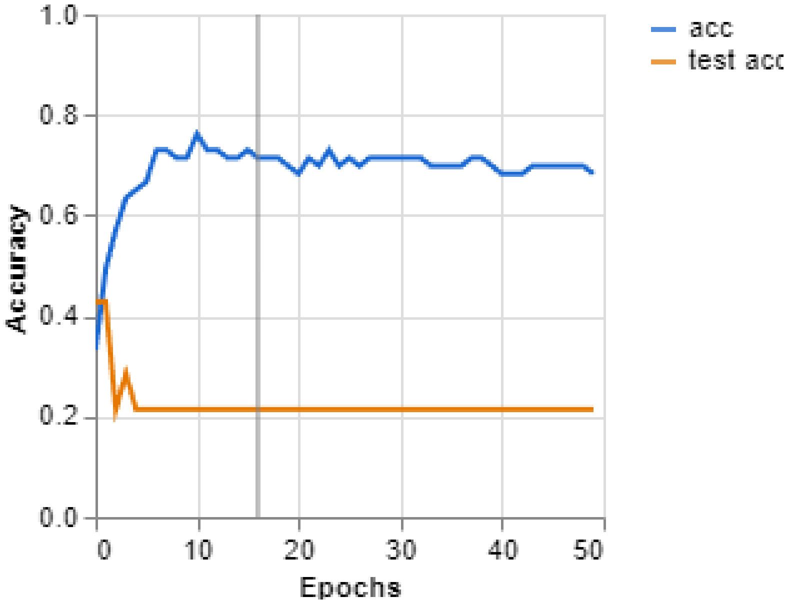


Figure 5.1 Accuracy Per Epoch

(X-axis) Epochs

In the Figure5.1 this axis represents the number of times the machine learning model has been trained on the entire dataset. As the number of epochs increases, the model is exposed to the training data more times, allowing it to learn and improve its performance.

(Y-axis) Accuracy

This axis represents the model's accuracy, which is the proportion of predictions that are correct. In the context of image classification, accuracy refers to how often the model correctly identifies the image category based on the image features it has learned.

(Orange Line)Training Accuracy

This line shows the model's accuracy on the training data after each epoch. Ideally, the training accuracy should increase steadily over time as the model learns from the training data.

(Blue Line)Validation Accuracy

This line (sometimes colored green or purple) shows the model's accuracy on a separate validation dataset. The validation dataset is not used to train the model, but rather to assess how well the model generalizes to unseen data. Ideally, the validation accuracy should also increase over time and closely follow the training accuracy **Table 5.1** trend.

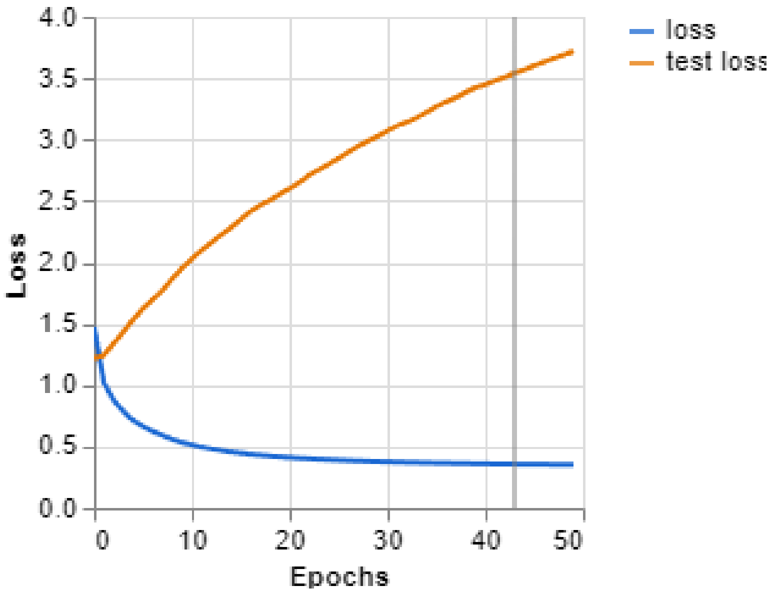


Figure 5.2 Loss Per Epoch

The Figure5.2 is a graph showing the training loss and test loss of a machine learning model over a number of epochs. The x-axis of the graph represents the number of epochs, which is one complete pass through the training data. The y-axis represents the loss value. The loss is a numerical value that indicates how well the model is performing on a given task. A lower loss value generally indicates better performance.

The blue line in the graph represents the training loss. This is the loss that the model is experiencing on the training data that it is being continuously trained on. The red line in the graph represents the test loss. This is the loss that the model is experiencing on a separate set of data that it has never seen before. The test loss is a more important metric than the training loss, as it is a better indicator of how well the model will generalize to unseen data.

In the Table5.1 you sent, the training loss (blue line) is decreasing over time, which suggests that the model is learning from the training data. However, the test loss (red line) is increasing over time. This suggests that the model is overfitting to the training data. Overfitting is a problem that occurs when a model learns the training data too well, and it is unable to generalize to unseen data.

Class	Accuracy	Samples
Brown Spot	1.00	29
Foolish Seedling	0.89	26
Healthy	0.78	25
Leaf Blast	0.98	22
Sheath Blight	0.75	19

Table 5.1: Table Of Accuracy Per Class

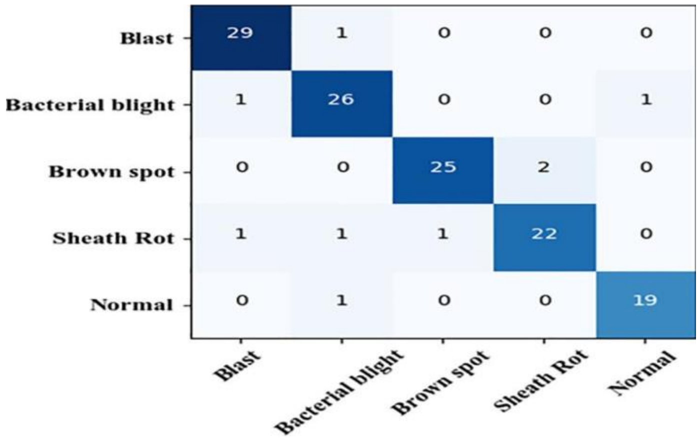


Figure 5.3 Matrix Analysis

The image **Figure5.3** is a confusion matrix, which is a table used to evaluate the performance of a machine learning model on a classification task. In this case, the task is classifying paddy plants according to different diseases.

The rows of the confusion matrix represent the actual diseases the paddy plants have, and the columns represent the diseases the model predicted the plants have.

An ideal confusion matrix would have high values along the diagonal, which means the model correctly classified most of the paddy plants.

Paddy Plant Diseases." This table focuses on how well the model identifies different diseases that can attack rice plants. It's like a detective trying to distinguish between various types of criminals.

Comparative Analysis of Deep Learning Models in Paddy Plant Disease Detection

This section provides a comprehensive comparison of four advanced deep learning models: Artificial Neural Network (ANN), Denoising Autoencoder (DAE), Deep Neural Network (DNN), and Deep Neural Network Joint Optimization Algorithm (DNN_JOA). These models are evaluated based on their performance in detecting diseases in paddy plants. The comparison is grounded on various metrics, including accuracy, F1-score, False Positive (FP), False Negative (FN) precision, True Positive (TP), and True Negative (TN). The objective is to identify the most effective model for accurate disease detection, thereby contributing to enhanced crop management and productivity.

Comparison of Model Accuracy

This subsection presents a graph Figure5.4 comparing the accuracy of ANN, DAE, DNN, and DNN_JOA in identifying paddy plant diseases. Accuracy is a crucial metric as it represents the overall effectiveness of the model in disease detection. By analyzing this graph, we can gain valuable insights into which algorithm delivers the highest success rate in disease detection, ultimately aiding in selecting the most reliable approach for real-world applications. Additionally, understanding the relative strengths and weaknesses of each model through accuracy comparisons can guide further research efforts towards developing even more precise disease identification techniques.

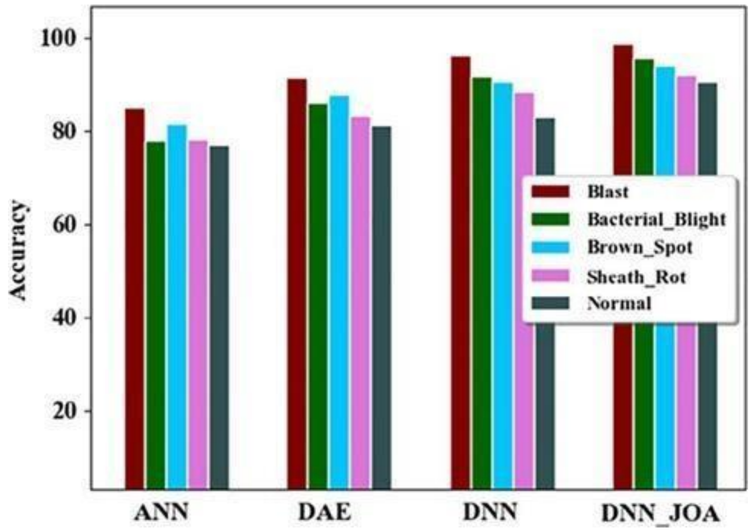


Figure 5.4 Comparison Of Model Accuracy

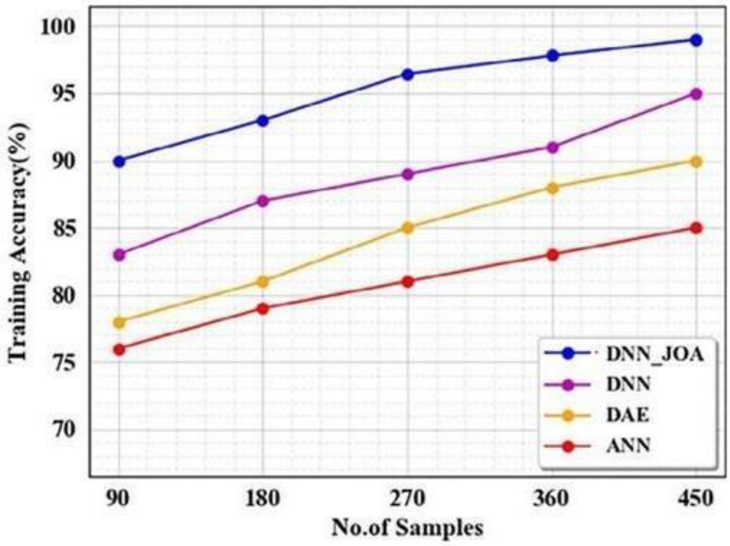


Figure 5.5 Training Accuracy

In the Figure5.5 Training accuracy in paddy plant disease models depends on the quality and size of the training data. Generally, a larger dataset with diverse rice plant diseases and clear, well-labeled images leads to higher accuracy. The model architecture itself also plays a role.

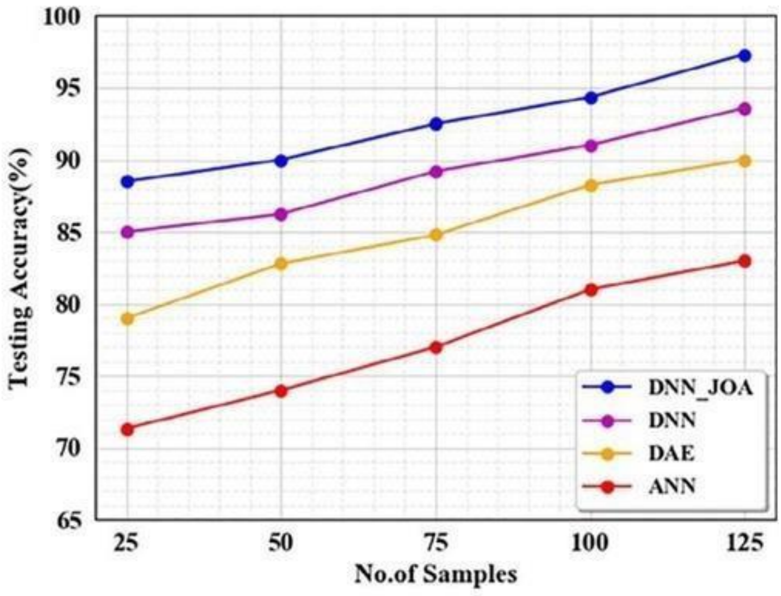


Figure 5.6 Testing Accuracy

The Figure 5.6 described likely shows a graph with lines representing the testing accuracy of different samples or models. The horizontal axis (x-axis) likely represents the number of samples tested, while the vertical axis (y-axis) likely represents the testing accuracy as a percentage.

Precision.

Deep learning boasts high precision in paddy disease detection. It analyzes images to consistently identify specific diseases, acting like a reliable fingerprint scanner for plant ailments. This allows for early intervention, empowering farmers to take targeted actions and minimize crop loss.

Precision = TP / (TP + False Positives)

False Positives (FP): Images incorrectly classified as diseased (healthy images classified as diseased).

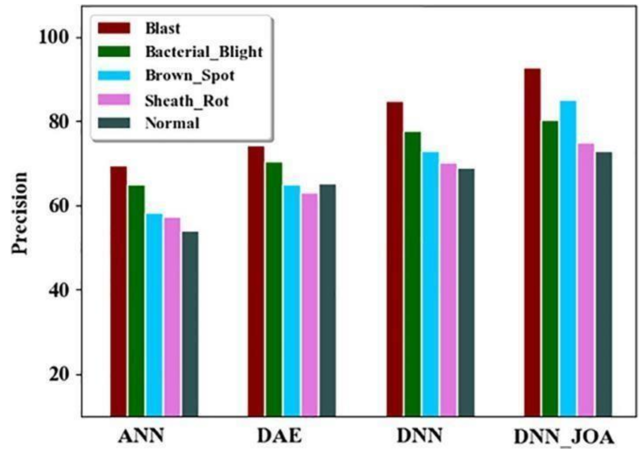


Figure 5.7 Comparison graph of precision.

In Figure 5.7 precision comparison elucidates the model's ability to return relevant results, with higher precision indicating a lower rate of false positives. This graph allows for a direct comparison of model precision in disease detection.

RECALL

This indicates the proportion of correctly identified diseased images out of all actual diseased images in the dataset:

Recall = TP / (TP + False Negatives)

False Negatives (FN): Images incorrectly classified as healthy (diseased images classified as healthy).

F1-Score

This harmonic mean combines precision and recall, providing a balanced view of model performance

F1-Score = 2 * (Precision * Recall) / (Precision + Recall)

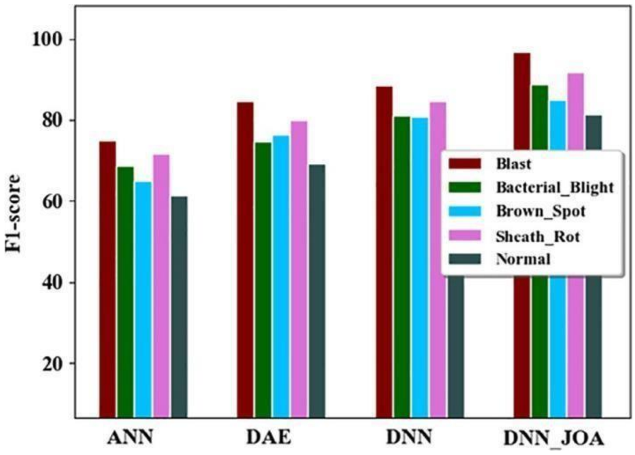


Figure 5.8 Comparison graph of F1-score.

In Figure 5.8 the F1-score, a harmonic mean of precision and recall, is analyzed here. A comparison graph illustrates how each model performs in terms of balancing precision and recall, indicating their reliability in disease classification.

REFERENCE	MODEL	ACCURACY (%)	RECALL (%)	PRECISION (%)	F1-SCORE(%)
Proposed	Deep learning (mobile net)	95.6	83	90	90
Vimal K. Shrivastava	CNN	90	85	80	81.5
U. Shruthi V. Nagaveni	Machine Learning	91	82	87	85
Shreya Ghosal; Kamal Sarkar	(CNN) Transfer Learning	92.42	81	80	81

Table 5.2 Model Performance on Paddy Plant Detection Using Deep Learning

Leaf type	Normal	Bacterial blight	Blast	Brown Spot	Sheath rot
Accuracy	90.57	95.78	98.9	94	92
F1-Score	81.25	88.75	96.86	85	91.86
Precision	73	80.4	92.8	85	75
Recall	80	81.2	83	80	75

Table 5.3 Classification Performance of Diseased and Normal leaf image.

RESULT AND DISCUSSION

Project uses deep learning, a powerful technology, to fight paddy plant diseases. Imagine taking a picture of your rice plants and the system instantly identifying problems like blast or blight. By analyzing massive image collections, the deep learning model becomes an expert at spotting diseases. This translates to earlier detection for farmers, allowing them to take action and save their crops before it's too late. This project has the potential to significantly improve rice production through faster and more accurate disease diagnosis.

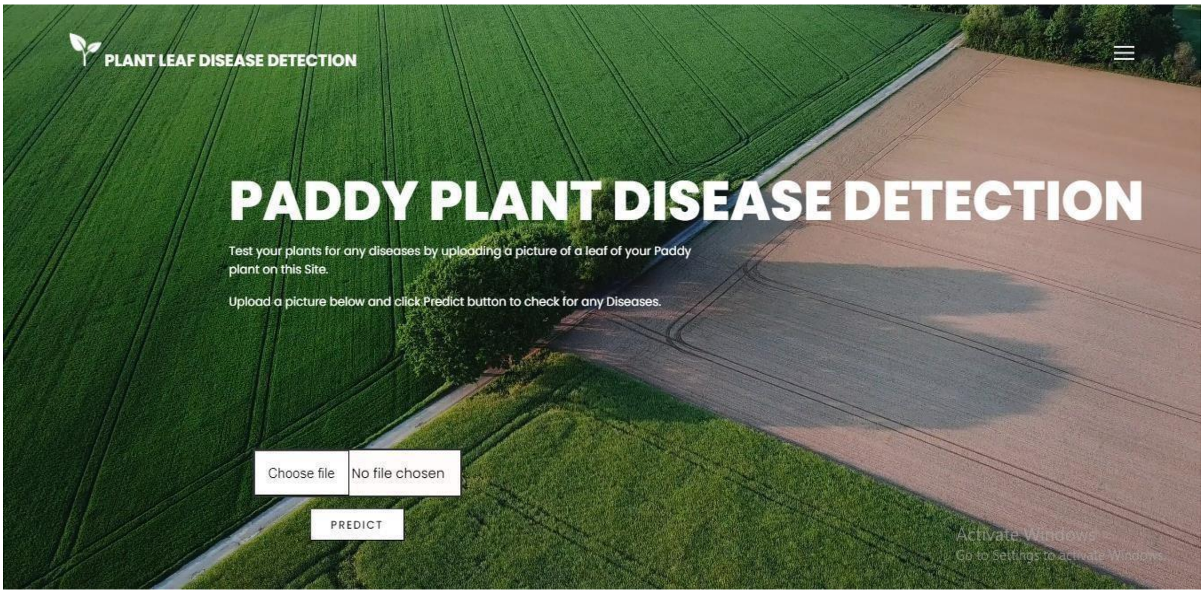


Figure 5.9 Index Page

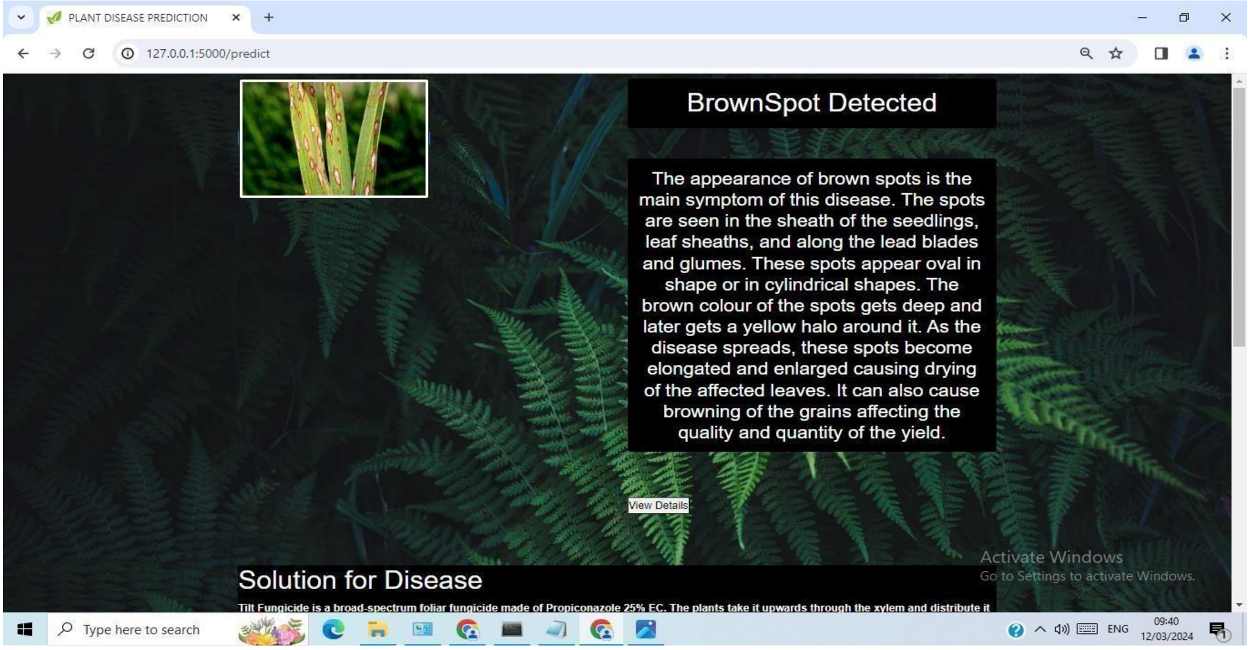


Figure 5.10 Brown Spot Detection

In the Figure 5.10 show Brown spot disease, caused by the fungus Bipolaris oryzae, haunts paddy fields, threatening both young seedlings and mature plants. This fungal villain can significantly reduce rice harvests. Watch out for small, oval brown spots appearing on leaves, their sheaths, and even the rice grains. If left unchecked, these spots can enlarge and merge, turning leaves brown and ultimately killing them. In severe cases, the entire plant can succumb. Brown spot not only slashes the number of grains produced but also diminishes their quality and weight. Moreover, it can be deadly to seedlings, hindering early growth. Historically, this disease has even been linked to devastating famines. The fungus flourishes in warm, humid environments with extended periods of leaf wetness. Additionally, rice plants lacking essential nutrients like nitrogen, potassium, or phosphorus become more susceptible.

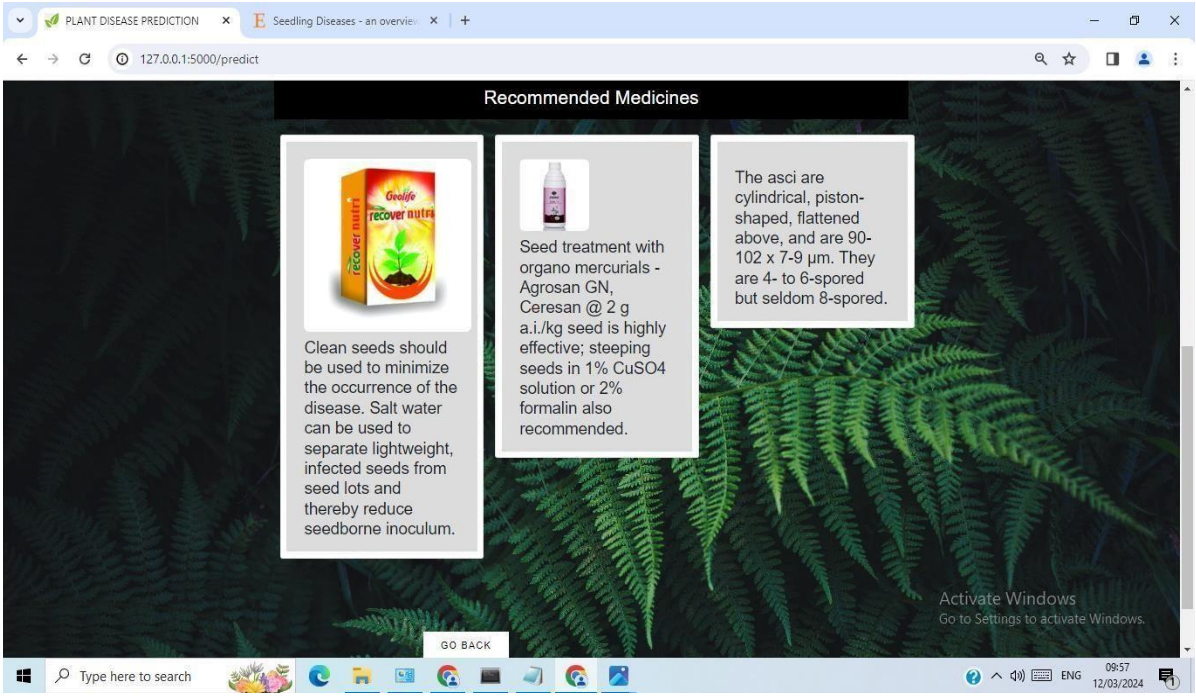


Figure 5.11 Foolish Seedling

In the Figure 5.11 show foolish seedling detection or bakanae in Japanese, can wreak havoc on your rice crop. This is not a case of playful plants, but rather the cunning work of the fungus Gibberella fujikuroi. This villain disrupts the rice plant's growth hormones, causing seedlings to grow excessively tall and thin. Imagine spindly, weak plants struggling to hold themselves upright – that is the hallmark of foolish seedling disease. Sadly, these stretched-out plants often topple over and die. Even survivors frequently produce empty husks instead of plump rice grains. This "foolish" growth significantly reduces crop yield, costing farmers precious resources and potential profits. By understanding foolish seedling disease

farmers can take steps to prevent this fungal foe from diminishing their harvest Foolish seedling disease, caused by the fungus Fusarium fujikuroi, poses a significant threat to rice production. Infected seedlings exhibit abnormal growth, with excessive elongation and a pale, weak appearance. This results in brittle stems that struggle to support the plant, and yellowing or browning leaves. Additionally, the disease reduces tillering, leading to a less dense and productive crop

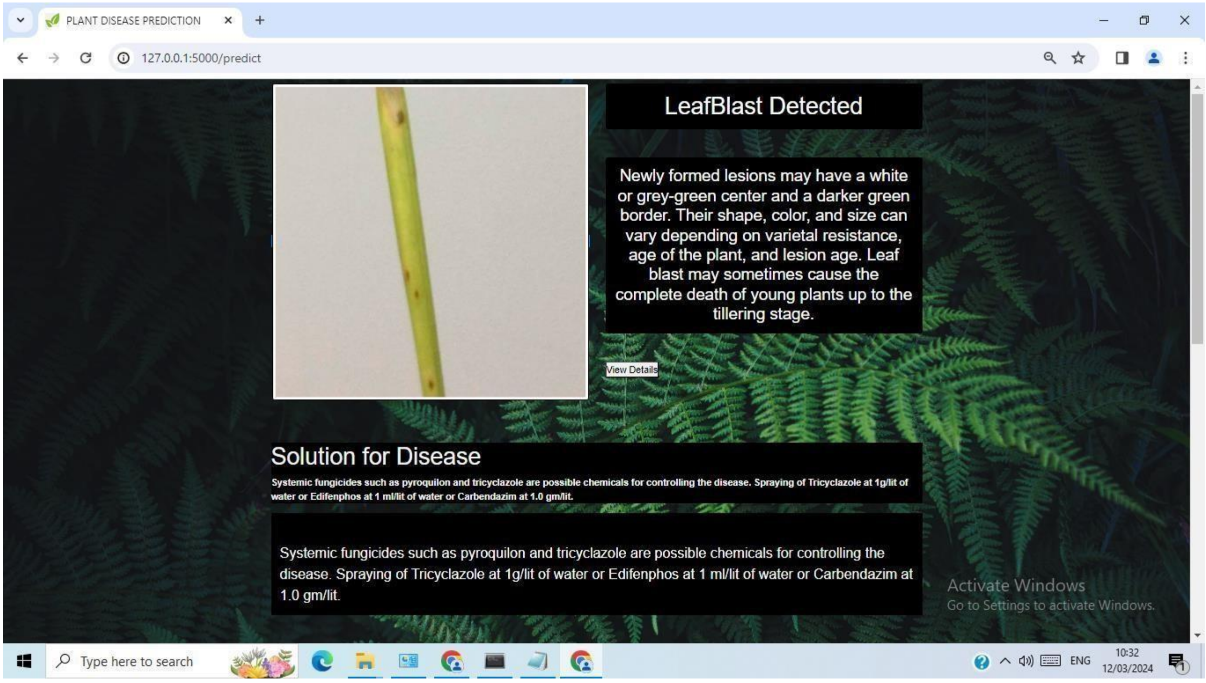


Figure 5.12 Leaf Blast

In the Figure 5.12 show Leaf blast, a fungal disease caused by Pyricularia oryzae, is a nightmare for rice farmers. This villain attacks all above-ground parts of the plant, from leaves and stems to developing grains. Watch for grayish-white spots with brown edges on leaves. These seemingly harmless marks can rapidly multiply, engulfing and killing entire leaves. In severe cases, the whole plant can be infected, leading to devastating yield loss. The damage doesn't stop there. Leaf blast weakens stems, making them more likely to fall over (lodge). Infected grains may also be discolored and shriveled, reducing both harvest quantity and quality. The fungus thrives in warm, humid conditions with wet leaves. Dense planting and excessive nitrogen use exacerbate the problem. Thankfully, there's hope. Planting resistant rice varieties and practicing crop rotation are crucial defenses. Balanced fertilization and proper water management can also help. In some cases, fungicides might be necessary, but use them strategically to minimize environmental impact. By understanding leaf blast, farmers can fight back and secure a bountiful harvest.

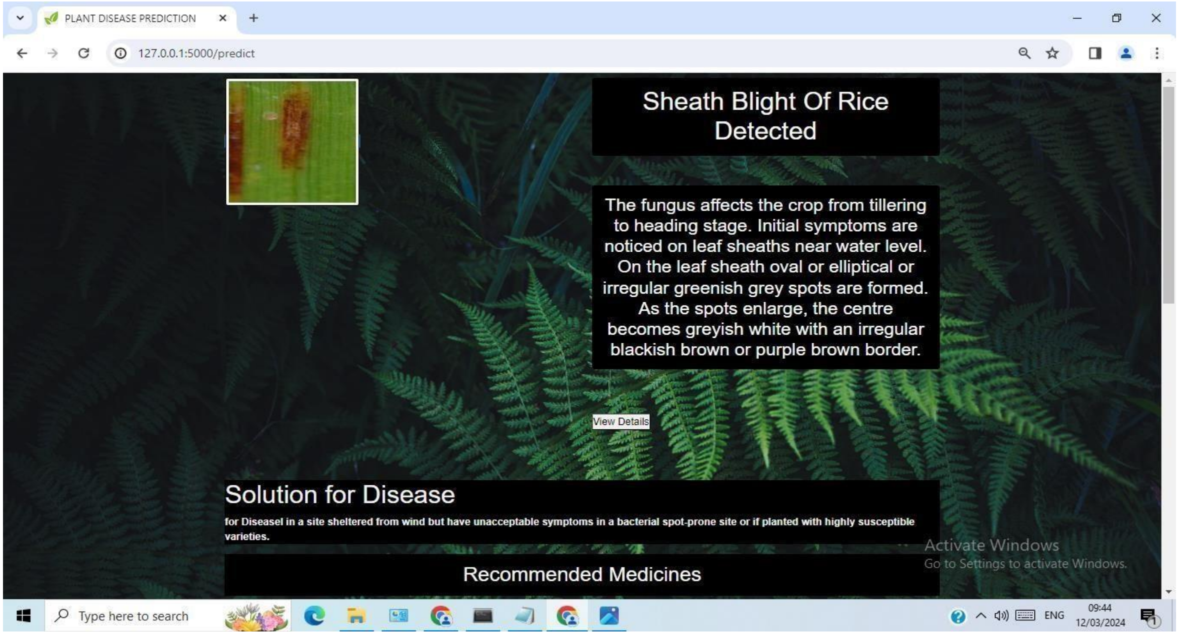


Figure 5.13 Sheath Blight Of Rice Detected.

In the Figure 5.13 show Sheath blight, a fungal disease caused by Rhizoctonia solani, has been detected in your rice fields. This disease poses a serious threat to your harvest. Be vigilant and inspect your plants for water-soaked lesions with grayish white centers and brown margins, particularly on the leaf sheaths and blades. The extent of these lesions indicates the severity of the disease. Early detection is crucial! Thankfully, there are ways to combat sheath blight. Consider using specific fungicides, but remember, prevention is key. Planting rice varieties naturally resistant to the disease is a long-term solution. Additionally, smart farming practices like proper water management, balanced fertilization, and removing crop residue after harvest can create a less hospitable environment for the fungus. Don't hesitate to seek further guidance from your local agricultural extension office or explore online resources for detailed information on managing sheath blight in rice. By taking swift action, you can minimize the damage and ensure a bountiful harvest.

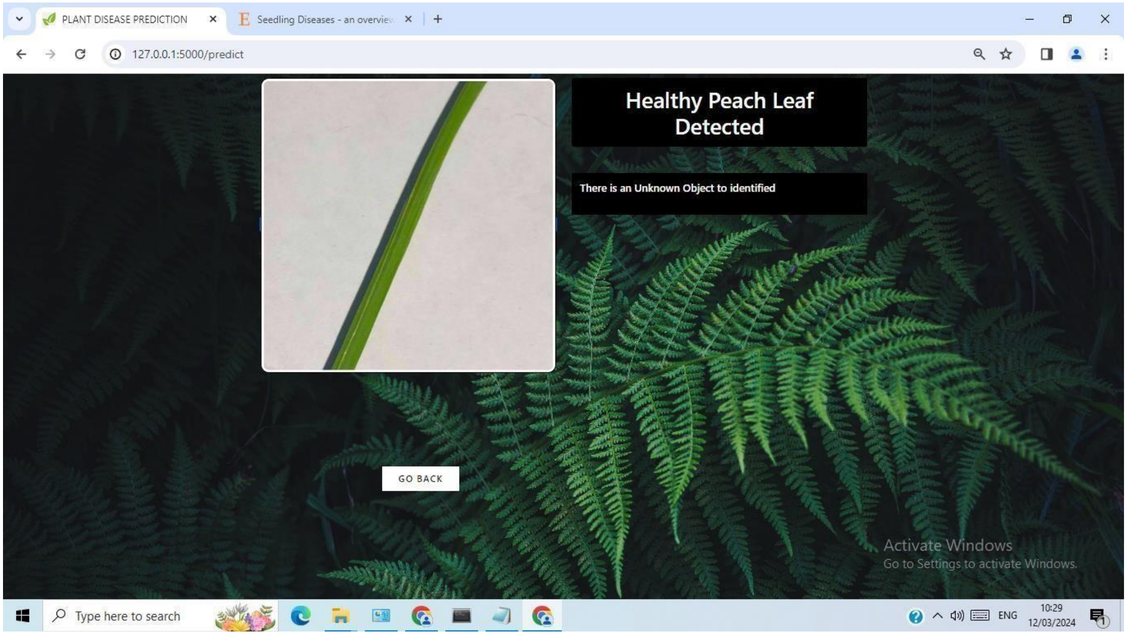


Figure 5.14 Healthy Peach Leaf Detected.

In the Figure 5.14 show Identifying healthy paddy plants involves assessing various indicators of vitality. Firstly, healthy plants display vibrant green leaves, devoid of yellowing or browning which may signify nutrient deficiencies or diseases. Their leaves should stand erect and not wilt, indicative of proper hydration and disease resistance. A strong, well-developed root system is essential, characterized by a fibrous network spreading evenly in the soil. Sturdy stems support the plant's weight, with no signs of bending or weakness. Vigorous growth is evident in tall plants with multiple tillers emerging evenly from the main culm. Moreover, healthy plants are relatively free from pest infestations and diseases, exhibiting uniform growth and well-formed panicles. Effective water management is also crucial to prevent stress from waterlogging or drought. Overall, assessing the color, structure, root health, pest/disease resistance, and growth patterns enables farmers to identify and maintain healthy paddy plants for optimal yield and crop quality.

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENT

6.1 Conclusion

Paddy cultivation faces a constant challenge: diseases that threaten crop health and yields. However, the emergence of machine learning, particularly with advancements like Mobile Net and image processing techniques, offers a powerful solution for farmers.

These technologies provide accurate disease detection, differentiating between healthy and diseased plants. Additionally, the ability to estimate the affected area through contour detection empowers farmers to assess the severity of the problem. Research has further explored the potential of deep learning algorithms, includingMobile Net, for classifying specific rice leaf diseases. This holds significant economic importance for regions heavily reliant on rice production, such as Bangladesh.

Looking ahead, the future of paddy disease management lies in further advancements. Future models can expand beyond basic disease classification to encompass a broader spectrum of issues, including nutrient deficiencies. Early stress detection can be achieved by refining deep learning algorithms to identify subtle signs before a full-blown disease develops, allowing for preventive measures.

The integration of powerful technologies like hyper-spectral imaging and the Internet of Things (IoT) holds immense promise. Hyper-spectral imaging can provide detailed data beyond the visible spectrum, enabling even more precise diagnoses. Integration with IoT sensors can offer real-time monitoring of paddy field conditions, providing valuable data for disease prediction.

Advanced decision-support systems, coupled with deep learning, can revolutionize treatment strategies. These systems can recommend customized plans based on the specific disease, paddy variety, and environmental factors, optimizing resource use and minimizing environmental impact.

Building trust with farmers is crucial. "Explainable AI" models that clearly explain their reasoning behind diagnoses and treatment recommendations are essential. User-friendly mobile applications will make this technology readily accessible, allowing farmers to capture images and receive real-time feedback directly on their smartphones.

In conclusion, advancements in machine learning for paddy disease detection mark a new era in proactive crop management. By embracing these future enhancements, we can create a robust system that empowers farmers to become guardians of their crops. This will lead to increased agricultural productivity, promote sustainable farming practices, and ultimately contribute to a more securefood supply for generations to come.

6.2 Application of the Project

The agricultural sector significantly contributes to the global economy, with rice serving as a staple food for over half of the world's population. However, diseases affecting paddy plants, such as blast, bacterial blight, and brown spot, can lead to substantial yield losses, threatening food security. Traditional methods of disease detection and management are time-consuming, labor-intensive, and often result in late diagnosis. This project introduces a novel application of deep learning to detect pathogens affecting paddy plants, offering a preventative approach to managing these diseases.

Real-time Disease Monitoring and Management

The deep learning model developed in this project allows for real-time monitoring of paddy fields through image analysis. Farmers can use drones or smartphones to capture images of their crops, which are then processed by the model to identify disease presence with high accuracy. This timely diagnosis enables farmers to apply targeted treatments, reducing the use of broad-spectrum pesticides and thereby minimizing environmental impact. Moreover, the system's predictive capabilities can forecast disease outbreaks based on historical data and current weather conditions, allowing for proactive disease management.

Precision Agriculture Integration

Integrating this deep learning model with precision agriculture technologies enhances its application further. Precision agriculture involves the use of technology to monitor and manage field variability in crops. By incorporating the disease detection model with sensors, GPS, and other IoT devices, farmers can receive localized data about the health of their crops. This integration facilitates precise application of fertilizers, pesticides, and water, optimizing resource use and improving crop health and yield.

Crop Insurance and Financial Planning

The accurate and early detection of plant diseases can also benefit crop insurance schemes. Insurance providers can use data from the deep learning model to assess risk more accurately, leading to more tailored insurance policies. Additionally, with reliable information on potential yield impacts due to diseases, farmers can make informed financial planning decisions, securing their livelihoods against the unpredictability of crop production.

Research and Development

This project's findings have significant implications for research in plant pathology and agronomy. By identifying disease patterns and their environmental correlates, researchers can develop more effective disease-resistant crop varieties. Furthermore, the accumulated data can enhance understanding of disease evolution, leading to improved management strategies.

Educational Outreach

Educating farmers on the importance of disease management and the use of technology in agriculture is crucial. Workshops and training programs can disseminate knowledge on operating the proposed system and interpreting its outputs. By empowering farmers with information and technology, this project fosters sustainable agricultural practices, contributing to global food security.

6.3 Limitations of the Major Project

The project focused on the detection of pathogens affecting paddy plants and a preventative method based on deep learning offers a novel approach to addressing crop diseases. However, despite its potential benefits, several limitations are inherent in its design, implementation, and broader applicability. This discussion delves into the critical limitations that may influence the project's effectiveness and scope.

Data Dependency and Quality

One of the primary limitations of this project stems from its heavy reliance on high-quality, annotated datasets for training and testing the deep learning models. The accuracy and reliability of disease detection are directly proportional to the quality and variety of the dataset used. In regions where such datasets are scarce or non-existent, the model's performance could significantly diminish. Furthermore, biases in the dataset can lead to skewed results, reducing the model's effectiveness in real-world applications.

Generalization and Scalability

While deep learning models excel in identifying patterns and making predictions based on the data they are trained on, they often struggle to generalize to new, unseen conditions. This limitation is particularly relevant when the model encounters plant diseases or pathogens not represented in the training dataset. Additionally, scalability issues may arise when attempting to apply the model to different rice varieties, growth stages, or geographic locations, as these factors can influence the manifestation of diseases.

Computational Requirements

Deep learning models, especially those involving complex neural networks, demand substantial computational resources for training and inference. This requirement can be a significant barrier for farmers or agricultural organizations with limited access to such resources. The need for powerful processors, adequate memory, and sometimes even specialized hardware like GPUs can make the implementation of these models impractical in resource-constrained environments.

Real-Time Processing Challenges

The project's effectiveness is also limited by its capacity for real-time disease detection and prevention. In large-scale farming operations, the ability to quickly identify and respond to disease outbreaks is crucial. However, the computational complexity of deep learning models can lead to delays in processing and analysis, potentially reducing the timeliness of interventions and diminishing the model's practical value in preventing crop loss.

Environmental Variability and Change

The performance of deep learning models in detecting paddy plant pathogens can be significantly affected by environmental factors such as lighting conditions, weather variations, and seasonal changes. These factors can alter the appearance of disease symptoms on plants, making it challenging for the model to maintain consistent accuracy. Adapting the model to dynamically account for such environmental variability remains a complex challenge.

Accessibility and User-Friendliness

The successful adoption of deep learning-based solutions for disease detection in agriculture heavily relies on their accessibility and ease of use by the end-users, typically farmers or agricultural workers. The complexity of deploying and operating such models can limit their applicability in the field, especially for users with limited technical expertise. Developing user-friendly interfaces and simplifying the model's deployment process are essential steps toward mitigating this limitation.

6.4 FUTURE ENHANCEMENT

Future Enhancements in Deep Learning for Paddy Disease Management

Deep learning has already revolutionized paddy disease detection, but its potential for future advancements is truly exciting. Here's a glimpse into what the future holds

Expanding Disease Detection Scope

Multi-disease and Deficiency Diagnosis

Models will move beyond identifying specific diseases to encompass a broader spectrum of issues. Imagine a model that can not only diagnose blast disease but also recognize nutrient deficiencies like iron chlorosis based on visual cues fromthe plant.

Early Stress Detection

Deep learning could be used to detect signs of early stress in plants, even before the onset of a full-blown disease. By identifying subtle changes in leaf color, texture, or growth patterns, the model could warn farmers of potential problems before they cause significant damage.

Integration with Advanced Technologies

Hyper-spectral Imaging

Deep learning can be combined with hyper-spectral imaging technology, which captures detailed information beyond the visible spectrum. This could give models a deeper understanding of plant health, enabling even more precise diagnoses.

Internet of Things (IoT) Integration

Imagine a network of paddy field sensors feeding real-time data on moisture, temperature, and nutrient levels into a deep learning model. This comprehensive data could allow the model to not only diagnose diseases but also predict their potential outbreaks based on environmental conditions.

Advanced Decision Support Systems

Precision Agriculture Solutions

Deep learning models could be integrated with decision support systems that recommend customized treatment plans. These plans could factor in the specific disease or deficiency detected, the paddy variety, and current environmental conditions. This would enable farmers to implement targeted interventions, optimizing resource use and minimizing environmental impact.

Predictive Maintenance

The model could analyze historical data and predict future disease outbreaks based on weather patterns and past occurrences. This would allow farmers to take preventive measures such as applying fungicides or adjusting irrigation practices,significantly reducing crop losses.

Explainable AI and User-Centric Design

Enhanced Transparency

"Explainable AI" will be crucial for building trust with farmers. Models should be able to explain their reasoning in a clear and user-friendly way, allowing farmers to understand the basis for the diagnosis and treatment recommendations.

Mobile App Integration

User-friendly mobile applications will make deep learning technology readily accessible to farmers. These apps could allow farmers to easily capture images of their paddy plants and receive real-time diagnoses and treatment recommendations directly on their smartphones.

ANNEXURE

SAMPLE CODE

IMPROVISED MAIN.PY

```
#Import necessary libraries
from flask import Flask, render_template, request


import numpy as np
import os


from tensorflow.keras.preprocessing.image import load_img
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.models import load_model


#load model
model =load_model("model/model1.h5")


print('@@ Model loaded')




def pred_cot_dieas(plant):
  test_image = load_img(plant, target_size = (128, 128)) # load image
```

```
  print("@@ Got Image for prediction")


  test_image = img_to_array(test_image)/255 # convert image to np array and
normalize
  test_image = np.expand_dims(test_image, axis = 0) # change dimention 3D to
4D


  result = model.predict(test_image) # predict diseased plant or not
  print('@@ Raw result = ', result)


  pred = np.argmax(result, axis=1)# get the index of max value
  print(pred)
  print('@@ Raw result2 = ', pred)


  if pred == 0:
    return "LeafBlast Detected", 'Cherry_powdery_mildew.html' # if index 0
burned leaf
  elif pred == 1:
      return 'Healthy Cherry Leaf Detected', 'healthy_plant.html'  # if index 1
  elif pred == 2:
      return 'Sheath Blight Of Rice Detected', 'Peach_Bacterial_Spot.html'  # if
index 2 fresh leaf
  elif pred == 3:
```

```
      return 'Healthy Peach Leaf Detected', 'healthy_plant.html'  # if index 3  fresh
leaf
  elif pred == 4:
      return 'BrownSpot Detected', 'Bell_Pepper_Bacterial_Spot.html'  # if index
4  fresh  leaf
  elif pred == 5:
      return 'Healthy Bell Pepper Leaf Detected', 'healthy_plant.html'  # if index 5
fresh leaf
  elif pred == 6:
      return 'foolish seedling Detected', 'Strawberry_Leaf_scorch.html'  # if index
6  fresh  leaf
  elif pred == 7:
      return 'There is not an proper image', 'healthy_plant.html'  # if index 7  fresh
leaf
  elif pred == 8:
      return 'Tomato mosaic virus Detected', 'Tomato_mosaic_virus.html' # if
index 8 fresh leaf
  else:
    return "Healthy Leaf Detected", 'Tomato-Healthy.html' # if index 9


# ----------- >>pred_dieas<<--end
```

```
# Create flask instance
app = Flask(__name__)


# render index.html page
@app.route("/aboutp")
def aboutp():
        return render_template('about.html')


@app.route("/infor")
def infor():
        return render_template('explore.html')


@app.route("/", methods=['GET', 'POST'])
def home():
        return render_template('index.html')



# get input image from client then predict class and render respective .html page
for solution
@app.route("/predict", methods = ['GET','POST'])
def predict():
    if request.method == 'POST':
```

```
        file = request.files['image'] # fet input
        filename = file.filename
        print("@@ Input posted = ", filename)

        file_path = os.path.join('static/user uploaded/', filename)
        file.save(file_path)

        print("@@ Predicting class ..... ")
        pred, output_page = pred_cot_dieas(plant=file_path)

        return render_template(output_page, pred_output = pred, user_image =
file_path)

# For local system & cloud
if __name___== "__main__":
    app.run(threaded=False,)
```

INDEX.HTML

```
@import
url('https://fonts.googleapis.com/css?family=Poppins:200,300,400,500,600,700,
800,900&display=swap');

*
{
  margin: 0;
  padding: 0;
  box-sizing: border-box;
  font-family: 'Poppins', sans-serif;
}
header
{
  position: absolute;
  top: 0;
  left: 0;
  width: 100%;
  padding: 40px 100px;
  z-index: 1000;
  display: flex;
  justify-content: space-between;
  align-items: center;
}
header .logo
```

```
{
  color: #fff;
  text-transform: uppercase;
  cursor: pointer;
}
.toggle
{
  position: relative;
  width: 60px;
  height: 60px;
  background: url(https://i.ibb.co/HrfVRcx/menu.png);
  background-repeat: no-repeat;
  background-size: 30px;
  background-position: center;
  cursor: pointer;
}
.toggle.active
{
  background: url(https://i.ibb.co/rt3HybH/close.png);
  background-repeat: no-repeat;
  background-size: 25px;
  background-position: center;
  cursor: pointer;
}
.showcase
{
```

```
  position: absolute;
  right: 0;
  width: 100%;
  min-height: 100vh;
  padding: 100px;
  display: flex;
  justify-content: space-between;
  align-items: center;
  background: #111;
  transition: 0.5s;
  z-index: 2;
}
.showcase.active
{
  right: 300px;
}

.showcase video
{
  position: absolute;
  top: 0;
  left: 0;
  width: 100%;
  height: 100%;
  object-fit: cover;
  opacity: 0.8;
```

```
}

.text
{
  position: relative;
  z-index: 10;
}

.text h2
{
  font-size: 5em;
  font-weight: 800;
  color: #fff;
  line-height: 1em;
  text-transform: uppercase;
}
.text h3
{
  font-size: 4em;
  font-weight: 700;
  color: #fff;
  line-height: 1em;
  text-transform: uppercase;
}
.text p
{
```

```
  font-size: 1.1em;
  color: #fff;
  margin: 20px 0;
  font-weight: 400;
  max-width: 700px;
}
.text a
{
  display: inline-block;
  font-size: 1em;
  background: #fff;
  padding: 10px 30px;
  text-transform: uppercase;
  text-decoration: none;
  font-weight: 500;
  margin-top: 10px;
  color: #111;
  letter-spacing: 2px;
  transition: 0.2s;
}
.text a:hover
{
  letter-spacing: 6px;
}
.social
{
```

```
  position: absolute;
  z-index: 10;
  bottom: 20px;
  display: flex;
  justify-content: center;
  align-items: center;
}
.social li
{
  list-style: none;
}
.social li a
{
  display: inline-block;
  margin-right: 20px;
  filter: invert(1);
  transform: scale(0.5);
  transition: 0.5s;
}
.social li a:hover
{
  transform: scale(0.5) translateY(-15px);
}
.menu
{
  position: absolute;
```

```
  top: 0;
  right: 0;
  width: 300px;
  height: 100%;
  display: flex;
  justify-content: center;
  align-items: center;
}
.menu ul
{
  position: relative;
}
.menu ul li
{
  list-style: none;
}
.menu ul li a
{
  text-decoration: none;
  font-size:  24px;
  color: #111;
}
.menu ul li a:hover
{
  color: #03a9f4;
}
```

```
@media (max-width: 991px)
{
  .showcase,
  .showcase header
  {
    padding: 40px;
  }
  .text h2
  {
    font-size: 3em;
  }
  .text h3
  {
    font-size: 2em;
  }
}
```

ABOUT.HTML

```
body {
   font-family: Arial, Helvetica, sans-serif;
   margin: 1;
   background: fixed;
   background-repeat: no-repeat;
   background-image: url("../static/images/1.jpg");
   background-size: cover;
  }

  html {
   box-sizing: border-box;
  }

  *, *:before, *:after {
   box-sizing: inherit;
   font-family: 'Poppins', sans-serif;
   }
```

```
.row{
   margin-left:      4em;
   display: inline-block;
}
.column {
  display: inline-block;
  margin-bottom: 9em;
  padding: 0 8px;
}

.card {
  box-shadow: 0 4px 8px 0 rgba(0, 0, 0, 0.2);
  margin: 4px;
  display: inline-block;
}

.about-section {
  padding: 1px;
  text-align: center;
  color: whitesmoke;
}
.about-section h2{
```

```
  margin-top: 50px;
  margin-bottom: 100px;
}

.container {
  padding: 0 5px;
}

.container::after, .row::after {
  content: "";
  clear: both;
  display: table;
}


.button {
  border: none;
  outline: 0;
  display: inline-block;
  padding: 8px;
  color: black;
  background-color: white;
```

```
  text-align: center;
  cursor: pointer;
  width: 80%;
}

.button:hover {
  color: black;
  background-color: white;
  width: 90%;
  letter-spacing: 4px;
  text-transform: uppercase;
}

@media screen and (max-width: 650px) {
  .column {
    width: 100%;
    display: block;
  }
}
.flip-card {
  background-color: transparent;
  width: 200px;
```

```
  height: 230px;
  border: 1px solid #f1f1f1;
  perspective: 1000px; /* Remove this if you don't want the 3D effect */
}

/* This container is needed to position the front and back side */
.flip-card-inner {
  position: relative;
  width: 100%;
  height: 100%;
  text-align: center;
  transition: transform 0.8s;
  transform-style: preserve-3d;
}

/* Do an horizontal flip when you move the mouse over the flip box container
*/
.flip-card:hover .flip-card-inner {
  transform: rotateY(180deg);
}

/* Position the front and back side */
```

```
.flip-card-front, .flip-card-back {
  position: absolute;
  width: 100%;
  height: 100%;
  -webkit-backface-visibility: hidden; /* Safari */
  backface-visibility: hidden;
}

/* Style the front side (fallback if image is missing) */
.flip-card-front {
  background-color: #bbb;
  color: black;
}

/* Style the back side */
.flip-card-back {
  color: white;
  transform: rotateY(180deg);
  background-size: cover;
}

.text a:hover {
```

```
  background-color: black;
  color: whitesmoke;
}

.text a {
  display: inline-block;
  font-size: 1em;
  background: #fff;
  padding: 10px 30px;
  text-transform: uppercase;
  text-decoration: none;
  font-weight: 500;
  margin-top: 20px;
  color: #111;
  letter-spacing: 2px;
  transition: 0.2s;
  margin-left: 43.3em;

}
```

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