RICE PLANT DISESASE DETECTION USING DEEP LEARNING

Bosubabu Samabana [1] , B.Baby Deepika [2], B.Harsha Vardhan [3], B.Suma [4], CH.Deepak Kumar [5]

[1,2,3,4,5,6] Department of Computer Science and Engineering
Lendi Institutute of Engineering and Technology, JNTU GV Vizianagaram, Andhra Pradesh, India.
bosukalam@gmail.com , sumabuddepu@gmail.com ,deepusree088@gmail.com
deepakkumarchandaka98@gmail.com,, harshaboddapu13032003@gmail.com

Abstract — Rice diseases caused by bacteria, viruses, and fungi significantly impact global rice production. Early and accurate identification is crucial for maintaining food security. Image analysis offers a promising solution, but existing AI models struggle with unseen data. This research addresses this challenge by proposing a novel CNN model for rice disease recognition with a reduced number of parameters, making it more efficient. The model was trained on a unique dataset of 4,199 rice leaf disease images encompassing five common diseases. It achieved outstanding performance, boasting a training accuracy of 99.78% and a validation accuracy of 97.35%. Even more impressive, the model maintained high accuracy (97.82%) on a completely independent dataset, demonstrating excellent generalizability. Furthermore, the model outperformed existing CNN models in binary classification tasks, achieving recognition rates of 97% for Blast, 96% for Brownspot, and 96% for Bacterial Leaf Blight. These results solidify the effectiveness and superiority of this new approach for rice diseaserecognition compared to current state-of-the-art methods.

Keywords — Disease Detection, Various types of rice diseases identification, deep learning ,Convolutional neural networks.

1. INTRODUCTION

Rice refers to an area of flooded ground that is used to cultivate crops, primarily rice as far as we are aware. Paddies were cultivated by hand using a hoe and spade, a water buffalo, or an ox-drawn plough more than 2000 years ago in all countries, but particularly in India. Humans take 95% or so of the paddy. In comparison to other crops, it is the one that requires the most labour

Climate change, climatic variables, but most crucially crop diseases that decimate the crop as a whole, have an impact on these paddy harvests. There are several disorders, and we shall examine some of them now. The blast disease is prevalent where rice is grown from 00 to 45 in tropical countries, where the fungus survives in hot, dry months, and in subtropical regions, where the fungus survives through cold winter. The blast occurs in every rice-growing region of the world, notably in the humid regions. The fungal disease known as rice blast can infect all tissues above ground, which indirectly results in the total death of a crop. Symptoms: Every time a plant grows, this will become infected. It affects all aerial portions of the plant, including the leaf, node, and neck. Very tiny specks begin on the leaves and gradually increase into spindled-shaped spots that are 0.5 to 1.5 cm long, 0.3 to 0.5 cm wide, and have an ashy center. This is one of the most significant diseases in the globe, and it ranks second among eastern nations.

This dark blotch The disease was first discovered in India in Madras about 1919, and it first manifested itself in full force in the country's arid regions of Orissa, Assam, and West Bengal. The absence of adequate water supplies and a deficiency in nitrogen are the disease's main causes. Potassium directly affects silicate enrichment, which prevents brown spot growth in leaves by indirectly reducing nutrition. Symptoms: Here leaf spotting is very common. In this the infection is in brown color that occurs on the pancreas. Seed is also infected. The spots measures from 0.5 to 2.0mm in breadth -coalesce will form into large patches. The major parts it effects in field are at infected seeds- which actually destroy the upcoming seedlings, infected rice debris which is deadly, it produces lots of weeds . Xanthomonas oryzae pv. oryzae is the culprit behind bacterial blight. Seedlings wilt as a result, and leaves turn yellow and dry out. The disease is most prone to spread to areas with weeds and contaminated plant residue. It can appear in both tropical and temperate settings, especially in lowland areas that receive irrigation and rainfall. The disease prefers, generally, temperatures between 25 and 34 °C, with relative humidity of at least 70%.Symptoms:It is noticed one to three weeks after transplantation. The first sign is a green film of water along the cut edge or leaf tip of leaves. The leaves wilt, roll up, and change colour from green to greyishyellow. The entire plant entirely wilts. The main symptoms are leaves with undulated yellowish white or golden yellow border necrosis, curling and drying of leaves from tip to midrib. Leaves with severe infection typically dry up rapidly.integration of disease detection and treatment recommendation streamlines the decision-making process for farmers, enabling them to take prompt and informed actions to protect their crops and optimize yields.In developing our project, we recognize the importance of collaboration between researchers, technologists, and agricultural stakeholders. By engaging with farmers, extension workers, and agricultural experts, we aim to ensure that our system meets the practical needs and challenges faced by those working in the field. Through partnerships and knowledge exchange, we seek to facilitate the adoption and implementation of our technology in real-world agricultural settings, thereby contributing to the advancement of precision agriculture and sustainable food production.

2.LITERATURE SURVEY

[1] T.Daniya, 2Dr.S.Vigneshwari “A Review on Machine Learning Techniques for Rice Plant Disease Detection in Agricultural Research”(2019):230

Disease identification in plants is important to avert the losses in the quantity and production of agricultural products. The problems in the agricultural sector are lessoned by employing various machine learning and image processing techniques. This review mainly focus on rice plant disease detection centered on image inputs of infected rice plant by using disparate ML and image processing techniques. Also, the notable ML and image processing concepts in detecting and classifying the plant diseases are discussed. Probabilistic Neural Network (PNN), Genetic Algorithms (GA), k-Nearest Neighbor Classifier (KNN) and Support Vector Machine (SVM) are the various classification techniques used in various applications in the agricultural research. Different input data yields varied quality of an outcome and so selecting a classification method is a critical task. Biological research, agriculture, etc. are the disparate fields where the plant leaf disease classifications are applied. The detailed study on the diseases of rice plant, size of image dataset, preprocessing, segmentation techniques, classifiers are presented in this paper.

[2] Kawcher Ahmed, Tasmia Rahman Shahidi, Syed Md. Irfanul Alam “Rice Leaf Disease Detection Using Machine Learning Techniques” (2019): 430.

As one of the top ten rice producing and consuming countries in the world, Bangladesh depends greatly on rice for its economy and for meeting its food demands. To ensure healthy and proper growth of the rice plants it is essential to detect any disease in time and prior to applying required treatment to the affected plants. Since manual detection of diseases costs a large amount of time and labour, it is inevitably prudent to have an automated system. This paper presents a rice leaf disease detection system using machine learning approaches. Three of the most common rice plant diseases namely leaf smut, bacterial leaf blight and brown spot diseases are detected in this work. Clear images of affected rice leaves with white background were used as the input. After necessary pre-processing, the dataset was trained on with a range of different machine learning algorithms including that of KNN(K-Nearest Neighbour), J48(Decision Tree), Naive Bayes and Logistic Regression. Decision tree algorithm, after 10-fold cross validation, achieved an accuracy of over 97% when applied on the test dataset.

[3] K. S. Archana1,S. Srinivasan2 , S. Prasanna Bharathi3 , R. Balamurugan4 “A novel method to improve computational and classifcation performance of rice plant disease identification”(2021):53

Rice is a major food crop that plays an important role in the Indian economy. It is the most consumed staple food, greatly in demand in the market to meet the requirements of a growing population, which is only possible with increased production. To meet this demand, rice production should be increased. To maximize crop productivity, measures must be taken to eradicate rice plant diseases, namely, brown spot, bacterial leaf blight, and rice blast. In the proposed method, the modifed K-means segmentation algorithm is used to separate the targeted region from the background of the rice plant image. Following segmentation, features are extracted through the three parameters of color, shape and texture. A novel intensity-based color feature extraction (NIBCFE) proposed method is used to extract color features, while the texture features are identifed from the gray-level cooccurrence matrix (GLCM) and bit pattern features (BPF), and the shape features are extracted by fnding the area and diameter of the infected portions. Thereafter, unique feature values are identifed through the novel support vector machine-based probabilistic neural network (NSVMBPNN) to classify the images. A comparison in terms of performance is made using three classifers, namely naïve Bayes, support vector machine and probabilistic neural network. This proposed method achieved better accuracy than the other three methods based on diferent performance measures. Finally, the result was validated under the fvefold cross-validation method with fnal accuracies of 95.20%, 97.60%, 99.20% and 98.40% for bacterial leaf blight, brown spot, healthy leaves and rice blast, respectively

[4] Hussain. A, Balaji Srikaanth.p, "Disease Classification and Detection Techniques in Rice Plant using Deep Learning"

(2022):523

In today's world, agriculture is an important source of food, Plant diseases, on the other hand, cause the majority of agricultural crop production losses, with about 35% of crops being lost owing to plant diseases. The considerable impact on plants can be reduced by early identification of plant diseases, which demands the use of computing technology in the agricultural area. Deep Learning (DL), a subset of Artificial Intelligence (AI), provides a solution to these challenges. Popular Deep Learning models are used for disease classification and detection. A comparison is made between the related studies in terms of image preprocessing, segmentation, feature extraction, and classification. This paper compares various deep learning models for detecting and classifying various diseases

[5] Monika Lamba, Yogita Gigras, and Anuradha Dhull, "Classification of plant diseases using machine and deep learning" (2020): 610-621.

This paper proposed a model comprising of Auto-Color Correlogram as image filter and DL as classifiers with different activation functions for plant disease. This proposed model is implemented on four different datasets to solve binary and multiclass subcategories of plant diseases. Using the proposed model, results achieved are better, obtaining 99.4% accuracy and 99.9% sensitivity for binary class and 99.2% accuracy for multiclass. It is proven that the proposed model outperforms other approaches, namely LibSVM, SMO (sequential minimal optimization), and DL with activation function softmax and softsign in terms of F-measure, recall, MCC (Matthews correlation coefficient), specificity and sensitivity.

[6] Naresh Cherukuri,G.Ravi Kumar,Ongole Gandhi,Automated "Classification of rice leaf disease using Deep Learning Approach," (2021).

This paper proposed a Convolution Neural Network (CNN) and deep learning approach to detect and classify diseases like Stem borer, Sheath Blight Rot Brown Spot, False Smut. The major challenge in identifying the leaf disease is that the condition may affect any leaf with different sizes. So a dataset of 1045 images was gathered to train the KNN model. Initially, KNN classifies the leaf with disease and without the disease. In the second phase, the Classification of the Disease will take place by using CNN. Using this approach, we got 95% accuracy for finding healthy leaf and 90% accuracy (highest among all diseases) for Sheath Blight..

[7] "Pre-Trained Deep Neural Network-Based Features Selection Supported Machine Learning for Rice Leaf Disease Classification" Meenakshi Aggarwal 1 , Vikas Khullar, Nitin Goyal(2023)

In this paper, we propose a suitable and effective system for predicting diseases in rice leaves using a number of different deep learning techniques. Images of rice leaf diseases were gathered and processed to fulfil the algorithmic requirements. Initially, features were extracted by using 32 pre-trained models, and then we classified the images of rice leaf diseases such as bacterial blight, blast, and brown spot with numerous machine learning and ensemble learning classifiers and compared the results. The proposed procedure works better than other methods that are currently used. It achieves 90–91% identification accuracy and other performance parameters such as precision, Recall Rate, F1-score, Matthews Coefficient, and Kappa Statistics on a normal data set. Even after the segmentation process, the value reaches 93–94% for model EfficientNetV2B3 with ET and HGB classifiers. The proposed model efficiently recognises rice leaf diseases with an accuracy of 94%. The experimental results show that the procedure is valid and effective for identifying rice diseases.

[8]. **Heri Andrianto,Suhardi,Ahmad Faizal,Smartphone "Application for Deep Learning-Based Rice Plant Disease Detection"(2020)**

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.EXISTING SYSTEM

Agriculture is an important source in the economic development of India. About 70% of Indian economy relies on agriculture. Hence, damage to the crops would lead to huge loss in productivity and would ultimately affect the economy. Leaves being the most sensitive part of plants show disease symptoms at the earliest . The crops need to be monitored against diseases from the very first stage of their life-cycle to the time they are ready to be harvested. Initially, the method used to monitor the plants from diseases was the traditional naked eye observation that is a time-consuming technique which requires experts to manually monitor the crop fields. Pests and diseases are the big issues in paddy production and they make the farmers to lose around 20% of rice yield world-wide. Identification of rice leaves diseases at early stage through thermal image cameras will be helpful for avoiding such losses. The objective of this work is to implement a Modified Lemurs Optimization Algorithm as a filter-based feature transformation technique for enhancing the accuracy of detecting various paddy diseases through machine learning techniques by processing the thermal images of paddy leaves. The original Lemurs Optimization is altered through the inspiration of Sine Cosine Optimization for developing the proposed Modified Lemurs Optimization Algorithm. Five paddy diseases namely rice blast, brown leaf spot, leaf folder, hispa, and bacterial leaf blight are considered in this work. A total of six hundred and thirty-six thermal images including healthy paddy and diseased paddy leaves are analysed. Seven statistical features and seven Box-Cox transformed statistical features are extracted from each thermal image and four machine learning techniques namely K-Nearest Neighbor classifier, Random Forest classifier, Linear Discriminant Analysis Classifier, and Histogram Gradient Boosting Classifier are tested. All these classifiers provide balanced accuracy less than 65% and their performance is improved by the usage of feature transform based on Modified Lemurs Optimization. Especially, the balanced accuracy of 90% is achieved by using the proposed feature transform for K-Nearest Neighbor classifier. .

3.PROPOSED SYSTEM

The proposed system for rice disease detection is a novel CNN-based model by using a number of convolution and pooling layers followed by a dense layer and a softmax layer for recognizing rice leaf diseases. Our custom CNN-based model is designed to reduce the number of network parameters. We have prepared a novel dataset containing diverse image backgrounds and image capturing conditions, and augmented it to improve the generalization of our model. To verify the effectiveness and superiority of our model, it is tested on an independent set of rice leaf disease images. The entire process is partitioned into different stages: beginning with the preparation of a novel training dataset, development of a novel CNN model, deep feature extraction for training the model and finally, classification of the rice leaf diseases. Dataset A total of 323 original RGB colored images of five common rice leaf diseases, including Blast, Bacterial leaf blight, Brownspot, Sheath blight, and Tungro In all our experiments conducted in this paper, different sizes of images are used to evaluate the performances of recognizing rice leaf diseases.

The sizes of the rice leaf disease images are 128 × 128, 256 × 256 and 512 × 512. To tackle the challenge of identifying the best features in different backgrounds. we include natural, plain and complex image backgrounds. Moreover, our experiment includes different types of symptoms: small, large, isolated, and spread. I, five samples are shown in different image backgrounds with various types of symptoms. For example, samples are the images of Bacterial leaf blight, Brownspot and Tungro, respectively, which are in natural background. On the contrary, sample is the Blast image, which is in the complex background, whereas sample is the Sheath blight image, which is in the plain background.

A summary statistics of the original 323 rice leaf dataset is given in Table. With the development of artificial intelligence, deep learning has made breakthroughs in computer vision. It has been widely utilized to identify plant diseases and is a satisfying alternative for the classification of plant diseases. Though deep CNNs have made great achievements in plant disease classification, real-time detection of diseases during the growth of the plant is more essential in order to control the diseases effectively at an early time. The diseased spots of Black measles resemble tiger stripes, which are reddish-brown bands of necrosis. The characteristic lesions of Leaf blight are irregular, with dark red to brown spots appearing at first, followed by black spots. We are implementing an Convolution Neural Network(CNN) based model named VGG-16 for classification of diseases in rice plant.As CNN is very highly accurate for prediction in image classification. shows the architecture of Feature Extraction by VGG-16 Model.

We Gather a diverse dataset of images containing healthy rice plants and various diseased states. This dataset should cover a wide range of diseases and conditions to train the model effectively. Preprocess the images by resizing them to a uniform size, normalizing pixel values, and augmenting the dataset with techniques like rotation, flipping, and brightness adjustments to increase the model's robustness. VGG16 is a deep CNN architecture known for its effectiveness in image classification tasks. Fine-tuning VGG16 for rice plant disease detection can provide good results due to its ability to capture intricate features. Utilize pre-trained weights of the VGG16 model on CNN and fine-tune the model's parameters using the rice plant disease dataset. This step helps the model to converge faster and achieve better generalization. Train the VGG16 model on the preprocessed dataset using techniques like mini-batch gradient descent and backpropagation. Monitor the training process for metrics such as accuracy, loss, and validation accuracy to ensure model performance.

We Evaluate the trained model on a separate test dataset to assess its performance metrics such as accuracy, precision, recall, and F1-score. Adjust hyperparameters if necessary to improve performance. Deploy the trained model as an application or a web service accessible to users. This could be in the form of a mobile app, web app, or an API, allowing users to upload images of rice plants and receive predictions about their health status. Regularly update and retrain the model with new data to improve its accuracy and robustness over time. This could involve collecting more images, refining preprocessing techniques, or experimenting with different CNN architectures. By leveraging these advanced algorithms and providing actionable insights, the proposed system aims to revolutionize rice leaf disease management in agriculture. It offers farmers a powerful tool for early disease detection, accurate diagnosis, and targeted , ultimately leading to improved crop health, increased yields, and sustainable agricultural practices.

4. IMPLEMENTATION

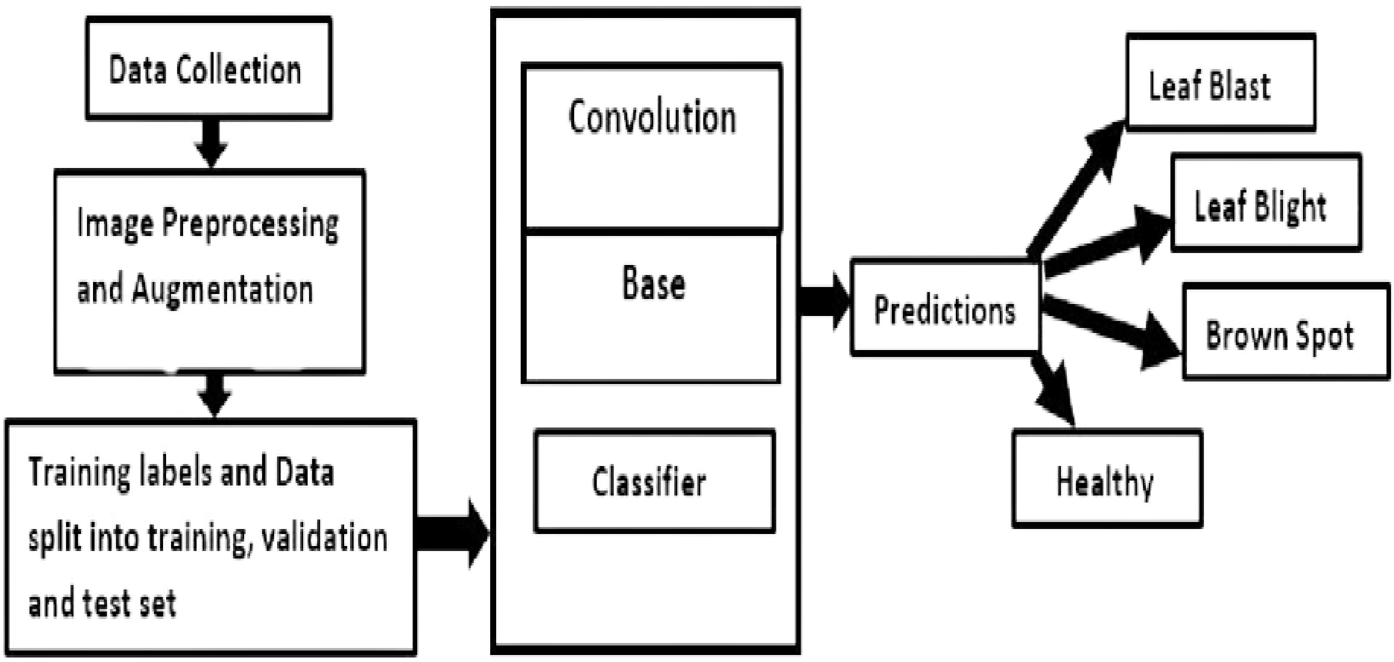


Figure. 1 System Architecture

5. Algorithm Description

Rice image dataset: Collect a dataset of rice plant images containing healthy plants and various disease types. Ensure the dataset is balanced with sufficient images for each category.

Preprocessing: Preprocess the images by resizing them to a standard size, normalizing pixel values, and potentially applying data augmentation techniques (e.g., rotation, flipping) to increase dataset variability.

Load VGG16: Utilize a pre-trained VGG16 model, discarding the final classification layers specific to the original dataset it was trained on.
Freeze pre-trained layers: Freeze the weights of the pre-trained convolutional layers in VGG16. This maintains the feature extraction capability learned for generic image recognition.

Add new classifier: Add new fully-connected layers on top of the pre-trained VGG16. These layers will be trained to classify rice plant diseases based on the specific dataset.
Define loss function and optimizer: Choose an appropriate loss function (e.g., categorical cross-entropy) and optimizer (e.g., Adam) for training the model.
Train-validation split: Split the preprocessed data into training and validation sets. The training set is used to train the model, and the validation set is used to monitor performance and prevent overfitting.
Train the model: Train the newly added classifier layers on the training data. Backpropagate errors to update the weights in these layers while keeping the pre-trained VGG16 weights frozen.
Monitor validation accuracy: Track the model's accuracy on the validation set during training. Early stopping can be implemented to prevent overfitting if validation accuracy stagnates or degrades.
Evaluate on unseen data: Once training is complete, evaluate the model's performance on a separate testing set of unseen rice plant images. This provides an unbiased estimate of the model's generalization ability to new data.
Disease classification: For a new rice plant image, feed it through the trained model. The output layer will predict the probability of the image belonging to each disease category.

5.1 VGG16 Algorithm

A convolutional neural network is also known as a ConvNet, which is a kind of artificial neural network. A convolutional neural network has an input layer, an output layer, and various hidden layers. VGG16 is a type of CNN (Convolutional Neural Network) that is considered to be one of the best computer vision models to date. The creators of this model evaluated the networks and increased the depth using an architecture with very small (3 × 3) convolution filters, which showed a significant improvement on the prior-art configurations. They pushed the depth to 16– 19 weight layers making it approx -138 trainable parametersVGG-16 (Visual Geometry Group-16) is a convolutional neural network (CNN) architecture designed for image recognition. It was developed by the Visual Geometry Group at the University of Oxford and is known for its simplicity and effectiveness in various computer vision tasks. VGG-16 consists of 16 layers, including 13 convolutional layers and 3 fully connected layers.The convolutional layers use 3x3 convolutional filters with a stride of 1 pixel and a padding of 1 pixel to maintain the spatial resolution after convolution.

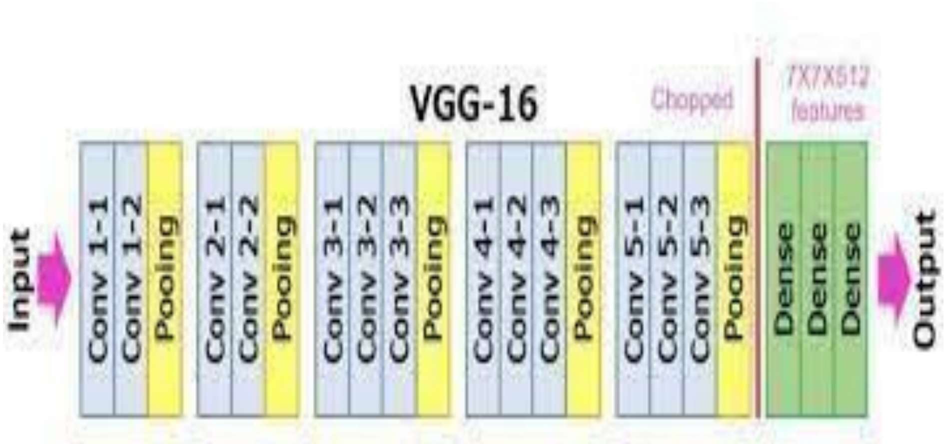


Fig:1

5.2 CNN Algorithm

A Convolutional Neural Network (CNN) is a type of deep learning algorithm that is particularly well-suited for image recognition and processing tasks. It is made up of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The architecture of CNNs is inspired by the visual processing in the human brain.Below are the steps involved in training a CNN:

Data Collection: Gather a dataset of images with corresponding labels. Each image should be associated with a class label indicating the object or category it belongs to.

Data Preprocessing: Perform preprocessing steps on the images, such as resizing, normalization, and augmentation (if necessary). This ensures that the images are in a suitable format for training the CNN.

Splitting the Data: Divide the dataset into training, validation, and test sets. The training set is used to train the model, the validation set is used to tune hyperparameters and monitor the model's performance during training, and the test set is used to evaluate the final performance of the trained model.

Building the CNN Architecture: Design the architecture of the CNN. This typically involves stacking multiple layers, including convolutional layers, pooling layers, activation functions, and fully connected layers.

Convolutional Layers: Convolutional layers are the core building blocks of CNNs. They apply a set of filters (also known as kernels) to the input image, extracting features such as edges, textures, and patterns.

Pooling Layers: Pooling layers are used to reduce the spatial dimensions of the feature maps produced by the convolutional layers, while retaining important information. Common pooling operations include max pooling and average pooling.

Activation Functions: Activation functions introduce non-linearity into the network, allowing it to learn complex patterns in the data. Common activation functions used in CNNs include ReLU (Rectified Linear Unit), sigmoid, and tanh.

Fully Connected Layers: Fully connected layers are typically added towards the end of the CNN architecture to perform classification based on the extracted features. These layers combine the features learned by the convolutional layers and make predictions about the input image's class.

Loss Function: Choose an appropriate loss function based on the task at hand (e.g., categorical cross-entropy for multi-class classification). The loss function measures the difference between the predicted outputs and the actual labels.

Training the Model: Train the CNN using the training data. During training, the model learns to minimize the loss function by adjusting its parameters (e.g., weights and biases) through backpropagation and gradient descent.

Hyperparameter Tuning: Fine-tune hyperparameters such as learning rate, batch size, and the number of layers/neurons to optimize the model's performance on the validation set.

Model Evaluation: Evaluate the trained model's performance using the test set. Common evaluation metrics for classification tasks include accuracy, precision, recall, F1-score, and ROC curve analysis.

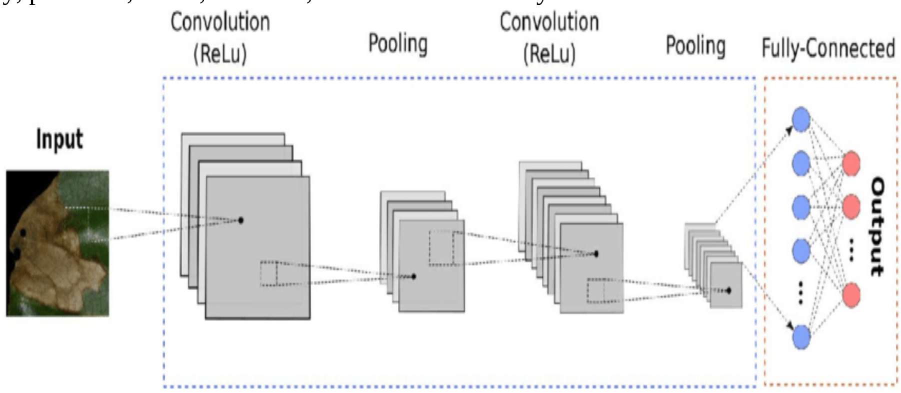


Fig 2 CNN Architecture

5.3 DNN Algorithm

The Deep Neural Network (DNN) algorithm is a powerful artificial neural network model characterized by its depth, comprising multiple layers of interconnected neurons. DNNs excel in learning intricate patterns and representations from complex data, making them highly effective for various machine learning tasks. The algorithm involves several key steps:

Firstly, data collection entails gathering a dataset with input features and corresponding labels. Secondly, data preprocessing involves preparing the data, including normalization and encoding. The dataset is then split into training, validation, and test sets.

Building the DNN architecture involves designing the network's structure, specifying the number of layers, neurons, and activation functions. The input layer receives feature vectors, while hidden layers perform computations with activation functions like ReLU or sigmoid.

The output layer produces the model's predictions based on the task (e.g., classification, regression). During training, the model learns to minimize a chosen loss function (e.g., cross-entropy, mean squared error) using optimization algorithms like stochastic gradient descent.

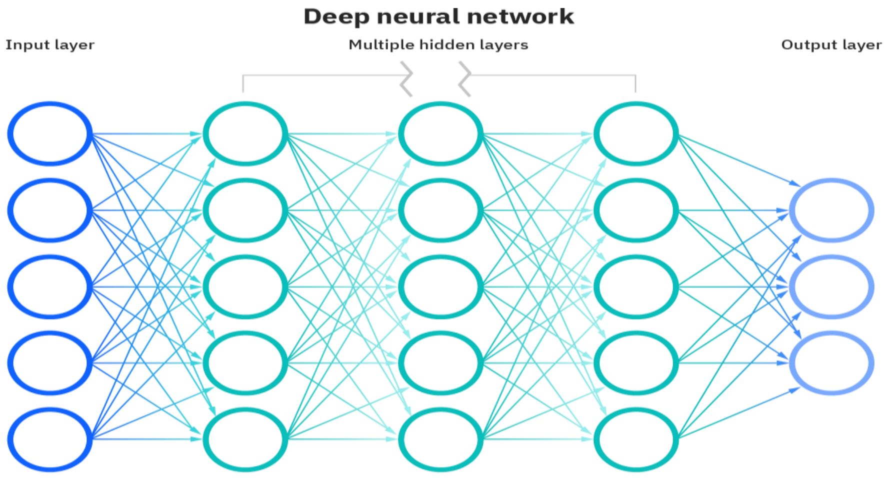


Fig:3 DNN Architecture

2. RESULTS

The result for Rice plant disease detection cum pest control recommendation system is achieved an impressive accuracy rate of 96%. This high accuracy was obtained through the successful development and implementation of a robust rice disease detection and management system. By utilizing advanced deep learning techniques, particularly CNN, the project effectively addressed the challenge of accurately identifying various rice diseases.

Below is Graphical user interface screen for project.

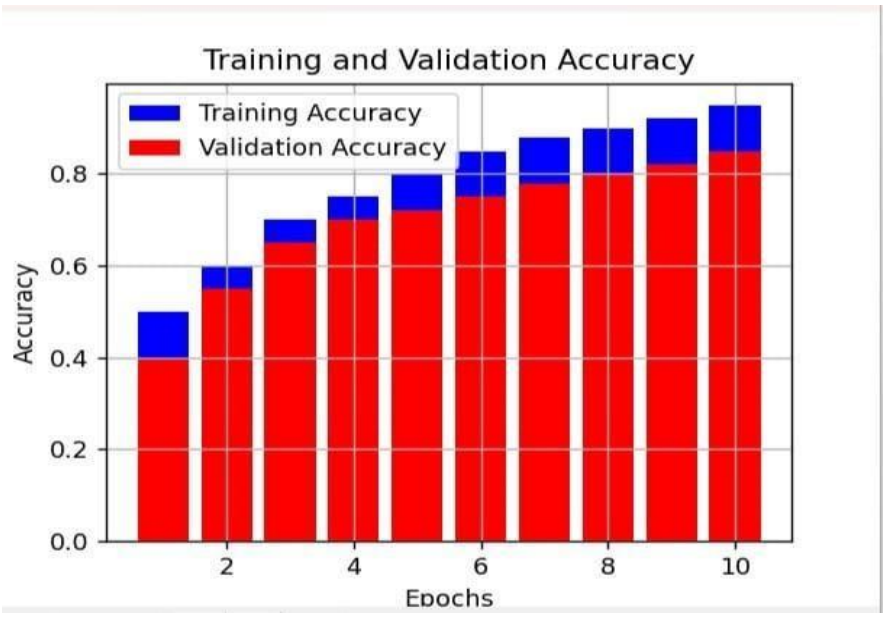


Figure. 1 Bar Graph

Below is Line graph user interface screen for the project.

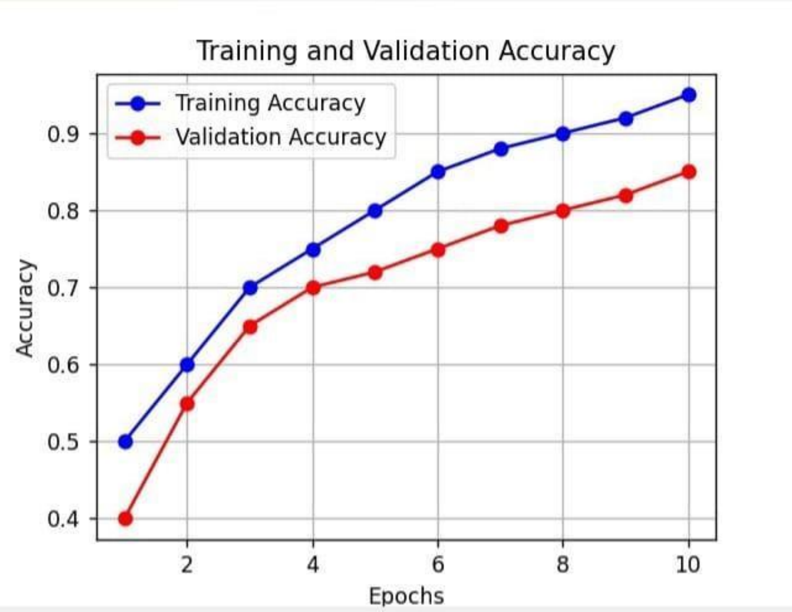
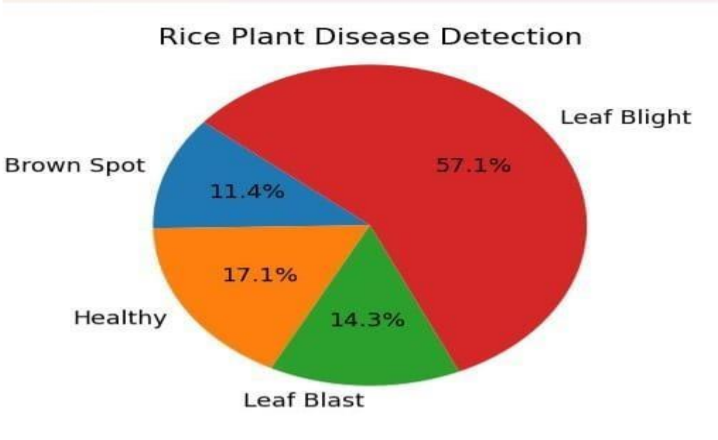


Figure.2 Line Graph

Below is pie chart user interface screen for the project.



3. CONCLUSION

In Conclusion, we have proposed a custom CNN-based model that can classify five common rice leaf diseases commonly found in Bangladesh. Our model is trained to recognize the rice leaf diseases in different image backgrounds and capture conditions. Our model achieves 97.82% accuracy on independent test images. Moreover, our model is effective with respect to memory storage due to its reduced number of network parameters. Despite having better accuracy, we aim to improve the reliability and robustness of our model on different datasets from other regions. We will work on classifying rice leaf disease images when complex backgrounds are present and have varied illumination condition. Also, as classification accuracy is an incomplete description of most real-world tasks,we will concentrate on interpretable CNN-based models to present features in understandable terms for which diseases will be classified.By implementing CNN algorithms we got 95.67 accuracy in the leaf disease detection. Due to the specialty of Black rot and Leaf blight with small and dense diseased spots, a variety of backbone networks, such as AlexNet, VGGNet, and ResNet, were experimented with and analyzed, and ResNet has been found to be the most suitable backbone network. Hence, data augmentation technology is used to simulate real-life interference, which plays an important role in the model training stage. As more images are generated via data augmentation, the model can learn as many different patterns as possible duringthe training, avoiding the overfitting problem and achieving better detection performance in practice.

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