Journal of Computer Science

Research Article

Automating Paddy Crop Disease Classification With Deep Learning Models

[1]Shiva Shankar J, [1]S. Palanivel and [2]S. China Venkateswarlu

[1]*Department of Electronics and Instrumentation Engineering, Annamalai University, Chidambaram, India*
[2]*Department of Electronics and Communication Engineering,Institute of Aeronautical Engineering, Hyderabad, India*

Article history
Received: 19-06-2024
Revised: 17-08-2024
Accepted: 27-08-2024

Corresponding Author:
Shiva Shankar J
Department of Electronics and Instrumentation Engineering,
Annamalai University,
Chidambaram, India
Email:
shivashankar.jss@gmail.com

Abstract: Rice is a staple food crop for more than 10 countries. High consumption of rice demands better yield of crop. Timely disease diagnosis in paddy is fundamental to preventing yield losses and ensuring an adequate supply of rice for a rapidly rising worldwide population. Agriculture and modern farming is one of the fields where IoT and automation can have a great impact. Maintaining healthy plants and monitoring their environment in order to identify or detect diseases is essential in order to maintain a maximum crop yield. The implementation of current high rocketing technologies including artificial intelligence (AI), machine learning, and deep learning have proved to be extremely important in modern agriculture as a method of advanced image analysis domain. Several studies showed that machine learning and deep learning technologies can detect plant diseases upon analyzing plant leaves with great accuracy and sensitivity. In this study, considering the value of deep learning for disease detection, two-dimensional convolutional neural network models - VGG-16, VGG-19, and ResNet50 - are presented to detect plant diseases, enabling farmers to take timely action regarding treatment without further delay. To carry this out, 3 different classes of plants diseases were chosen, where 2,871 plant leaf images were acquired from the real time dataset for training and testing. Based on the experimental results, the proposed model is able to achieve an accuracy of about 99.43% with ResNet50 compared to other models like 2D-CNN, VGG-16 and VGG-19.

Keywords: Paddy Disease, VGG-16, VGG-19, ResNet50

Introduction

Agriculture has been essential to human survival since its inception, serving as the primary source of food through plant cultivation. Today, it continues to be a vital component of global food security and plays a central role in various aspects of human life. Healthy crops are crucial for providing high-quality food for daily consumption and form the economic backbone of many countries, regardless of their development status. Notably, almost 70% of people on the planet get their living from agriculture, highlighting the sector's vital importance in feeding the world's expanding population. Global food security and food production are seriously threatened by plant diseases. Issues such as infections, insufficient monitoring of rice fields, and frequent paddy leaf diseases significantly impact rice yields and lead to substantial production losses. Paddy leaf diseases, in particular, are a major factor contributing to reduced production. Additionally, the rapidly changing climate is likely to exacerbate these problems, potentially causing widespread damage and failing to meet production standards and market demands. To address these challenges, researchers across various disciplines are developing new technologies to help farmers quickly and accurately detect and manage diseases in plants. Computer-assisted picture classification with machine learning support and deep learning offers an effective solution for this task. Computer vision, a specialized field within Artificial Intelligence, employs deep learning and neural network-based algorithms for autonomously analyzing, categorizing, and detecting images. This technology is capable of processing still images, video footage, and real-time visuals, making it a valuable tool for early disease detection and management in agriculture.

Diseases of Paddy Crops

Paddy crop will be affected by many diseases from its plantation stage to the yield stage. The effect of damage by the diseases clearly shows its results on the final yield. This paper is focused on three major diseases that come across in paddy crops; bacterial blight, blast and tungro which is shown in Figure 1.

Fig. 1: Diseases of Paddy Crop

Bacterial Blight: One of the most damaging diseases that paddy crops can suffer from is bacterial blight, which is brought on by Xanthomonas oryzae pv. oryzae.It results in yellowing and drying of the leaves and wilting of seedlings.The disease can result in significant yield losses if it strikes early in the crop's growth.

Blast: Known to be highly destructive, it is a disease conferred by the fungus Magnaporthe oryzae with an attack on all structures of the rice plant that are aerial. An infestation may affect the leaf, collar, node, neck, parts of the panicle, and, at times, the leaf sheath. This blast results in the death of the seedlings or tillering plants when the leaves are attacked. Later on, serious infections destroy the entire area where leaves can grow and develop into grains, thus leading to low yields. They suffer yield losses, sometimes very big ones, depending on when the disease attacks, for instance, when it attacks the seedling stage.

Brown Spot: Coffee brown spot is a fungal disease that attacks the coleoptile leaves, particularly the leaf sheaths and the branches of the panicle, glumes, and spikelets. The disease is accompanied by large, identifiable stains on the leaf, in the middle of which the entire leaf may die out. If infection takes place in the seeds, then it leads to poor grain filling or seeds that are either speckled or stained. Brown spot can be developed on rice at all growth stages; however, at the maximum tillering stage up to the ripening stages, the disease is most influential.

Tungro: Tungro is a disease that is attributed to the infection of two viruses through the medium of leafhoppers. It results in conditions like leaf blanching, slow growth, reduced tillering, and shrinkage of grains, which can either be sterile or partly filled. In addition to farmed rice, this disease also affects several wild rice varieties and other grassy weeds that are frequently found in rice fields. This is more severe in South and Southeast Asia; it reduces yield by up to 100% in poor varieties if infection starts early. Since the bug species that transmit the disease have a preference for young rice plants and are more likely to feed off infected young plants than mature ones, it is easily transmitted in young rice plants.

For the categorization of paddy diseases, this study used a pre-trained deep neural network classifier with VGG16, VGG19, and ResNet50 architectures. The method concentrated on categorizing three different paddy crop diseases from real time data which is gathered and prepared from Karimnagar District of Telangana State in India. Videos were taken for each disease and converted into frames.

Major Contributions of the Research

1. A novel approach to classification: A unique use of 2D-CNN, VGG16, VGG19, and ResNet50 models for the image-based categorization of several paddy crop illnesses is shown in this work
2. Improved expertise and yield: The suggested models outperform current methods in identifying and categorizing paddy illnesses, resulting in increased crop productivity and disease control

Related Works

Swathika *et al.* (2021) presents an idea to efficiently separate healthy paddy plants from those infected and further determine the specific part of the plant affected by a disease in the case of the latter category. 3,500 photos showing both healthy and sick paddy plant leaves make up the dataset. The classification module utilizes convolution layers based on neural networks and provides slightly over 70% accuracy. The paper starts with a description of the existing literature regarding CNN for image classification and presents a novel module for the classification of paddy diseases and guidelines for future work in this field.

Debnath and Saha (2022) proposed an intelligent model for the early identification of Brown Spot disease in rice paddies in order to minimize large financial losses in the agriculture industry. The model integrates Machine Learning with IoT technologies, employing a Convolutional Neural Networks (CNN) for disease detection, a novel approach in Smart Farming. TensorFlow and Keras frameworks are used for training and testing, while specially created image-processing tools are used to process real-time data. The model has a remarkable 97.701% accuracy rate, offering the potential to minimize losses in national and global rice production. Additionally, an accompanying mobile app has been developed so that farmers can have easy access.

Dhiman and Saroha (2022) suggest that a CNN-based approach that makes use of edge detection techniques is used for the identification and classification of paddy leaf diseases. It handles three different scenarios: no disease detected, detectable but curable disease, and severe, incurable disease. There are 650 images in the collection, 95 of which are normal and 125 of which exhibit symptoms of bacterial blight. The suggested method delivers a remarkable 97.692% total accuracy, demonstrating superior precision and recall accuracy compared to existing methods. This makes it a more accurate, adaptable, and scalable solution for disease detection in paddy leaves.

Pal (2021) uses a CNN-based strategy with pre-trained models including ResNet-50, ResNet-101, VGG-16, VGG-19, EfficientNet, Inception-V2, and GoogleNet, the method focuses on recognizing different illnesses that damage rice crops. The ReLU model enhances accuracy and efficiency in disease identification. The system aids farmers in diagnosing paddy leaf conditions swiftly and accurately, reducing the need for costly and time-consuming laboratory procedures. Achieving a maximum accuracy of 96.27% with the ResNet-50 pre-trained library, the system shows promise in maximizing paddy production while minimizing diagnostic costs and time. Expanding the dataset could further enhance accuracy.

The agricultural sector, which is crucial for Indonesia's economy, faces challenges in maintaining rice quality and production due to diseases. Purbasari *et al.* (2021) analyzes leaf photos to identify rice plant illnesses using Convolutional Neural Networks (CNN), a type of deep learning. CNN processes two-dimensional data through layers like convolution, sub-sampling, and fully connected layers. Four types of rice leaf diseases were examined using 2,239 training images per disease. The study achieved a promising training accuracy of 91%, demonstrating the potential of CNN in automated disease detection.

The agricultural economy of Bangladesh is heavily reliant on crop yield, making disease detection crucial to mitigate economic losses. With a focus on methods including picture capture, preliminary processing, categorization, extraction of features, and grouping, Hossain *et al.* (2022) investigates crop disease detection. Using Convolutional Neural Networks (CNN) with two hidden layers and an SGD optimizer, the technique detects paddy illnesses from input photos with a prediction accuracy of 73.33%.

Malvade *et al.* (2022) further describe the technique discussed in the study, which means that in abiotic stress identification of paddy crops, the researchers utilized the existing architecture of the convolutional neural models for a binary classification purpose. They contribute to the task of comparing the mentioned several CNN architectures that integrate the transfer learning with the InceptionV3 ImageNet weights, VGG16, ResNet50, DenseNet-121, and MobileNet-28. Three prevalent and harmful biotic stressors that impact paddy crops are the subject of the experiment. Some of these diseases are Leaf Blast, Hispa, and Brown Spot. Outcomes clarified that the ResNet-50 model gave the general misfortune estimations of the degree of 92 per cent of general misfortunes, which are commonly the superior rate of classification.

Narmadha *et al.* (2022) present a novel Deep Learning (DL) method called DenseNet169-MLP for diagnosing diseases in rice plants, aimed at easing the workload for farmers and reducing economic losses. This method detects illnesses, including bacterial leaf blight, brown spot, and leaf smut, by combining a multilayer perceptron (MLP) with a densely convolutional neural network (DenseNet). Channel separation, grayscale conversion, and Median Filtering (MF) noise reduction are all part of the preprocessing procedures. Images of rice plants are segmented using fuzzy c-means (FCM) to identify the unhealthy areas. The DenseNet169, pretrained as a feature extractor, works in tandem with the MLP, which replaces the final layer for classification. This model achieves a remarkable accuracy of 97.68%, surpassing the performance of existing methods.

Suseno *et al.* (2023) state that rice farming is essential to Indonesia's food security, yet farmers usually struggle to pinpoint the variables influencing rice yield promptly. To stop productivity reductions, rice plant illnesses must be identified early. To categorize rice leaf diseases, machine learning-specifically, Convolutional Neural Networks (CNN) like VGG16 has been used. Image segmentation techniques aid in simplifying the analysis by transforming image data into more manageable formats. The detection of rice leaf diseases, particularly bacterial leaf blight, brown spots, and leaf smut, is the main goal of this study. It applies various segmentation methods, including thresholding and k-means clustering, to isolate these diseases. To further enhance dataset diversity, data augmentation is employed. The VGG16 model, optimized through hyperparameter tuning, achieves an accuracy of 91.66% when evaluated on the k-means segmented dataset.

Recently, Deep Convolutional Neural Networks (DCNNs) have significantly advanced the classification and recognition of rice leaf diseases. However, existing models often extract features globally, potentially leading to lower accuracy as they may include redundant or low-correlation information from the lesion area. Bi & Wang (2024) suggest a Double-Branch DCNN (DBDCNN) model combined with a Convolutional Block Attention Module (CBAM) to overcome this difficulty. Compared to more conventional models like VGG-16, ResNet-50, ResNet50+CBAM, MobileNet-V2, GoogLeNet, EfficientNet-B1, and Inception-V2, the findings show a superior accuracy of 98.73%. These results imply that the DBDCNN model provides improved performance in categorizing and diagnosing rice leaf illnesses due to its novel approach to crop disease diagnosis.

India, a leading producer of paddy, saw a 33% increase in paddy export rates in 2021 compared to previous years, highlighting its significance in the country's Gross Domestic Product (GDP). Paddy is a crucial crop in Indian food production, yet it is susceptible to various diseases throughout its growth stages. Early disease detection is vital to minimize damage and enhance production quality and quantity. Major diseases such as Brown Spot, Sheath Rot, Sheath Blight, Rice Blast, and False Smut have a substantial impact on paddy production. With the use of computer vision and deep learning models, specifically

DOI: 10.3844/jcssp.2025.1772.1784

Convolutional Neural Networks (CNN), Vignesh & Elakya (2022) seek to identify and forecast early indications of these diseases in paddy. Among four primary classifiers with an accuracy of 95.3%, the Inception-V3 model outperformed the VGG16, VGG19, and ResNet50 models,proving its superior effectiveness in disease detection.

Hasan *et al.* (2023) introduces a compact CNN architecture for the efficient detection of rice leaf diseases, addressing the challenge of high computational costs associated with deep learning techniques. By reducing background noise through the use of image processing techniques like k-means clustering and segmentation, the accuracy of the model is increased. Trained on a 2700-image dataset and 1200 samples for validation, the model achieves a testing accuracy of 97.9%. Moreover, its deployment in a mobile application demonstrates practical, real-world utility. Comparative analysis showcases the model's competitiveness against existing solutions, affirming its reliability and effectiveness in rice disease classification.

Thamarai *et al.* (2024) describes a Convolutional Neural Network (CNN) that uses the ResNet-50 architecture to classify crop diseases with an astounding 97% accuracy rate. Through meticulous dataset curation, data augmentation, and model customization, an effective tool for disease detection in agriculture is developed. Fine-tuning of the model, including adjusting the learning rates of specific layers, further enhances its performance. The potential of deep learning to transform agriculture is shown by this study, offering a valuable resource for farmers and agronomists. Enabling timely and accurate identification of paddy diseases contributes to improved crop yields and loss mitigation.

In Malaysia, rice production is crucial for meeting the dietary needs of millions, yet challenges such as pests and diseases hinder optimal yields. Traditional methods of disease identification are slow and costly, requiring specialist intervention. Leveraging Deep Learning, Zainorzuli (2023) aims to classify paddy diseases like brown spot, leaf blast, and hispa using CNN models. Comparing ResNet-50, AlexNet, and GoogleNet, despite having somewhat longer processing times, ResNet-50 performs best in terms of accuracy, precision, recall, and F1 score. With accuracy exceeding 90%, ResNet-50 proves to be the most reliable model enabling early disease identification in rice farming, offering encouraging opportunities to raise Malaysia's agricultural output.

Imrankhan *et al.* (2024) examines how well Deep Convolutional Neural Networks (DCNN) and transfer learning work together to detect diseases in the leaves of rice plants. Using the ResNet50 technique with transfer learning, training time is reduced while enhancing network capabilities. With an accuracy of 81.8% using a Quadratic SVM classifier, various techniques are employed to classify rice leaf disease images. The paper emphasizes deep learning's potential in disease identification, achieving a remarkable disease accuracy rate of 98%.

Zhang *et al.* (2023) introduced an advanced object detection framework for recognizing paddy diseases, addressing issues such as severe overlap, multi-disease detection, and morphological irregularities. Building on an enhanced Detection Transformer (DETR) algorithm, the model integrates a feature fusion module and a deformable attention module to boost detection accuracy and minimize computational complexity. The results of testing on a specific dataset were impressive, with 100% precision, 89.3% recall, and 94.3% F1-score. This framework's accuracy outperforms that of current state-of-the-art methods, demonstrating its usefulness in actual paddy disease detection scenarios.

Vamsee Kongara *et al.* (2022) address the significant problem of disease diagnosis in paddy crops that is very vital for Indian farmers. Through the use of deep learning techniques, including Convolutional Neural Networks (CNN), transfer learning, and picture preprocessing, this strategy seeks to accurately and efficiently identify specific illnesses such as Bacterial Leaf Blight, Hispa, Brown Spot, and Leaf Blast. Comparing such pretrained models as InceptionV3, VGG16, and ResNet50, it is possible to conclude that InceptionV3 serves as the best one with the given accuracy of 91.23%. As a result, this work offers a useful model for early illness prediction, assisting farmers in safeguarding their harvests and promoting food security.

Mogilicharla and Mummadi (2024) states that to reduce the economic impact of diseases and pests that influence rice agriculture, it is essential to identify them. This paper presents a novel method that combines deep learning with traditional learning methods to improve the detection rate, building on the most recent advancements in CNNs. Two novelty models are proposed, both combinations of ResNet-50 and SVM, and one model is specifically, through experiments in this paper, the AuPCAs and the ShPCAs show the efficiency of detecting rice diseases and pests. A comparison between the proposed Model-1 and Model-2 depicts that the latter gives an improved accuracy of 93%.

By using artificial intelligence, namely deep learning techniques in computer vision, to improve paddy production, Anuar *et al.* (2022) addresses difficult issues related to food security. This study focuses on detecting defective seedlings, a critical but often overlooked aspect of optimal planting density. By evaluating various deep convolutional neural network (DCNN) models using aerial imagery, pretrained object detectors with one or two stages are tested in the study using feature extractors like ResNet50, EfficientNet and MobileNetV2 in conjunction with transfer learning. The methods achieve high precision (0.83) and F1-Score (0.77), with EfficientDet-D1 EfficientNet showing the best performance, highlighting the potential of deep learning to advance agricultural practices.

In order to reliably recognize and classify nine paddy diseases as well as healthy plants, Attallah (2023) presents "RiPa-Net," a pipeline that makes use of three lightweight CNNs. The Dual-Tree Complex Wavelet Transform (DTCWT) is used in the model to integrate spectral-temporal information and combine characteristics from two levels of each CNN. Dimensionality reduction is achieved using PCA and DCT transformation, followed by feature selection to streamline recognition. Experimental results show an impressive accuracy of 97.5% with the cubic support vector machine (SVM) and 300 features, demonstrating RiPa-Net's superior performance in paddy disease recognition.

Materials

Videos taken from rice fields in Telangana, India's Karimnagar District were utilized to construct the dataset for this study. An Apple iPad Air (4th Generation) with a 12 MP rear wide camera that can record 4K video at up to 60 frames per second and 1080p HD video at up to 60 frames per second was used to record the films, guaranteeing high-resolution data acquisition.

To create still photos that depicted various stages of illness presentation, captured movies were subsequently processed by removing frames at regular intervals. Three kinds of paddy leaf diseases, Bacterial Blight, Blast, and Tungro were manually assigned labels to the resultant photos.

The 2,871 photos in the dataset are divided into 2,296 training images and 575 testing images.

The iPad Air (4th Generation) has a resolution of roughly 1080 x 1440 pixels when each image was first taken from the video frames. Each image was downsized to the usual input size required by the VGG16 convolutional neural network, which is 224×224×3 pixels, to guarantee compatibility.

Resizing the photos preserves enough quality for precise feature extraction while drastically lowering memory and computational cost. Additionally, it permits uniform input dimensions throughout the dataset, which is essential for batch processing and effective deep learning model training.

Python was used for all image preprocessing, training, and assessment in a high-performance computing environment utilizing the TensorFlow and Keras packages.

Methods

Developing a method for recognizing rice plant illnesses is the aim of this work using 2DCNN, VGG16, VGG19 and ResNet50 models. The proposed system detects diseases of plants like Bacterial blight, Blast and Tungro using the rice plant diseases video frames. The main steps involved in this work is as follows: Dataset collection, converting videos to frames, training the 2D-CNN model,VGG16,VGG19 and Resnet50 model, followed by testing the models. Figure 2 displays the suggested system's block diagram.

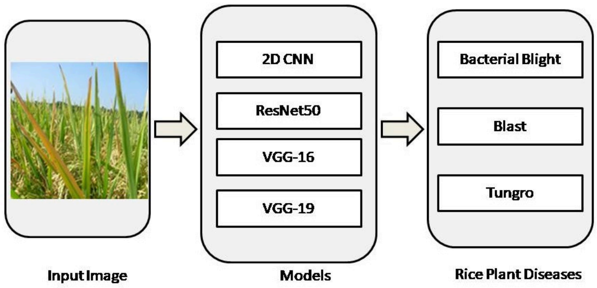

Fig. 2: Block Diagram of the Deep Learning Based Paddy Crop Disease Classification Model

Preprocessing Images

Image resizing and normalization are crucial preprocessing procedures for agricultural image analysis, particularly the identification of paddy diseases because they maximize the data for more accurate results and efficient processing. Resizing images to a smaller, optimal size reduces the computational power and memory required for processing. Tasks like filtration, extraction of features, and identifying objects become more efficient as a result of this improvement, guaranteeing quicker and more accurate results.

Normalizing the values of pixels to an established range (such as 0-1 or 0-255) after resizing guarantees uniformity for the processing stages that follow. The following is the comprehensive algorithm for downsizing and normalizing photos of paddy disease.

Step 1: Load the Image
Function: load_image(image_path)
Input: image_path (path to the paddy disease image file)
Output: Loaded image I
Step 2: Change the Picture to Grayscale
Function: Grayscale(I)
Input: Image I
Output: Grayscale image I_gray
Step 3: Resize the Image
Function: Resize(I_gray, width, height)
Input: Grayscale image I_gray, width = 224, height = 224
Output: Resized image I_resized
Step 4: Normalize the Image
Function: Normalize(I_resized)
Input: Resized image I_resized
Output: Normalized image I_normalized with pixel values in the range [0, 1]

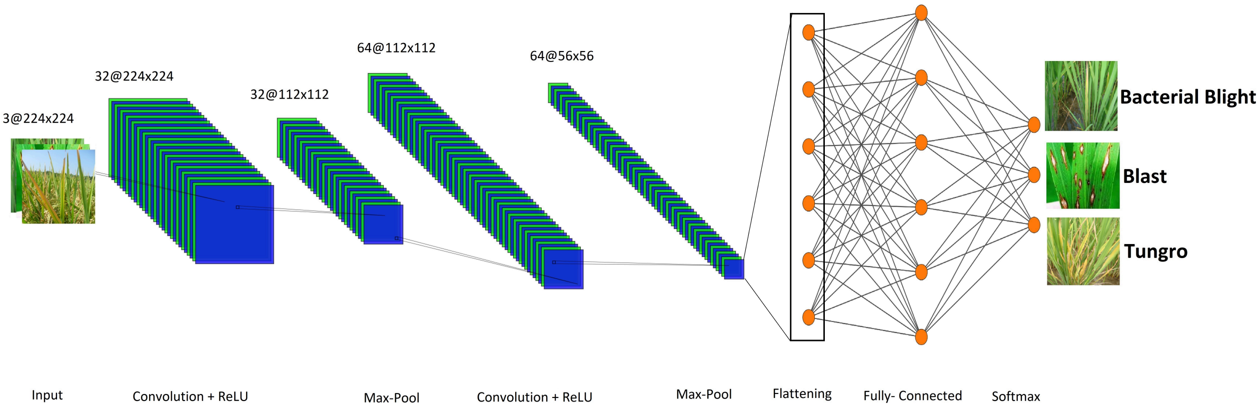

Fig. 3: 2D - CNN Architecture Used in the Proposed Work (Quy Thanh, 2023)

2-D CNN

Input Layer

As illustrated in Figure 3, a Convolutional Neural Network (CNN) consists of multiple hidden layers, an input layer, and an output layer. Applications for CNNs are numerous and include computer vision, natural language processing, medical image analysis, image classification, and image and video recognition. Colour images contain three colour channels (RGB), while grayscale images have a single channel. The number of pixels a filter traverses through the input image during convolution is known as its stride. The filter advances one pixel at a time when the stride value is set to 1 and two pixels at a time when the stride value is set to 2. The usage of padding helps regulate the size of the output and prevent information loss that occurs when the output size decreases due to convolution. Padding involves adding zeros around the input border. There are two common padding types: "same," which maintains the size of the output matches that of the input size, and "valid," which implies no padding is applied. Eq. 1 represents the convolution operation, while Eq. 2 computes the feature map size, as shown in Figure 4.

$$y_{Conv} = f\left(\sum_{j=0}^{j=1}\sum_{i=0}^{i=1} x_{m+i,n+j} w_{ij} + b\right)\left(0 \le m \le M, 0 \le n \le N\right) \quad (1)$$

$$Feature\ map\ Size = \left(N - F + 2P\right)/S + 1 \quad (2)$$

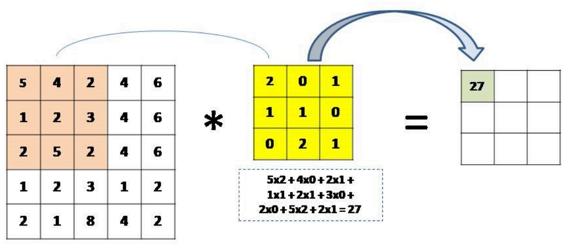

Fig. 4: Example of 2D CNN Architecture with Convolutional Layer

Max Pooling Layer

After convolution layers, CNNs frequently employ the pooling layer operation, which has the goal of reducing the dimension, also known as downsampling (Iparraguirre-Villanueva *et al.*, 2023). Max pooling is used in the pooling layer to minimize the size of the feature map while preserving the most significant features by choosing the highest possible values from the feature mapping. Eq. 3 illustrates max pooling and is shown in Figure 5.

$$f_{pool} = Max\left(x_{m,n}, x_{m+1,n}, x_{m,n+1}, x_{m+1,n+1}\right)$$
$$\left(0 \le m \le M, 0 \le n \le N\right) \quad (3)$$

In the formula, the f_{pool} represents the maximum pooling result of the feature graph.

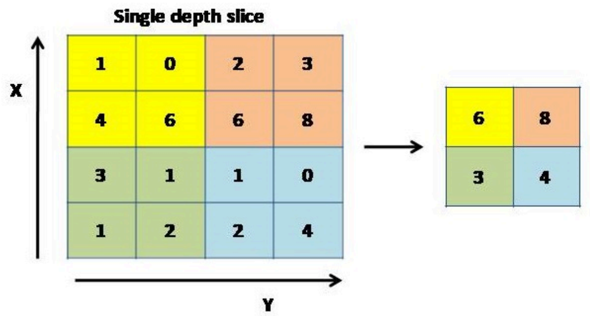

Fig. 5: Example of 2D CNN Architecture with Max Pooling Layer

Features in a Convolutional Neural Network (CNN) are transmitted to the Fully Connected (FC) layer after being processed by convolutional and pooling layers. In order to make the resulting 2-dimensional arrays from the pooled feature maps acceptable for input into fully connected layers, they are flattened into a single, continuous linear vector (Taujuddin *et al.*, 2021, Thomkaew & Intakosum, 2022). This flattened vector is then used in the FC layer. Dropout, which randomly sets a portion of the input units to zero during training, is used to reduce overfitting and enhance the model's

DOI: 10.3844/jcssp.2025.1772.1784

generalization. Dropout randomly deactivates a fraction of neurons during training, preventing the network from relying too heavily on any single neuron. By applying a threshold to the input, the activation function specifies whether a neuron must be activated, contributing to the model's non-linearity and normalizes the output of each neuron within a specific range. In 2D CNNs, common activation functions include Sigmoid, tanH, Softmax, and ReLU. The Rectified Linear Unit (ReLU) activation function is used in this work. It offers several advantages: it replaces negative values in the feature map with zero, has infinite maximum threshold values, mitigates the vanishing gradient problem, and enhances prediction accuracy and computational efficiency. Additionally, ReLU operates faster than other activation functions. The ReLU activation function is represented by Eq.4 and is illustrated in Figure 6.

$$\begin{aligned} Max(0,x) &= x, \quad x \geq 0 \\ &= 0, \quad x < 0 \end{aligned} \tag{4}$$

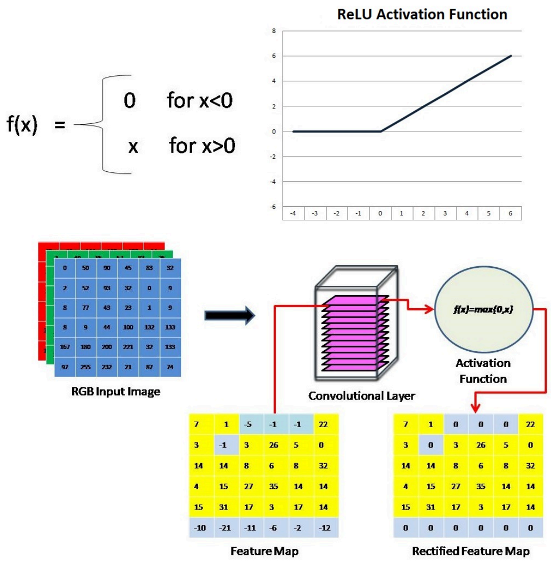

Fig. 6: Example of 2D CNN Architecture with Relu Activation Function (Zaki *et al.*, 2021)

Dense Layer, or Fully Connected Layer

- Every neuron in this layer is linked to every other neuron in the layer above. This layer is typically used towards the end of the network to create final predictions by combining the characteristics that the convolutional and pooling layers have learned
- Activation Function: Often uses softmax for classification tasks

Output Layer

The last network layer that produces the output forecasts. A softmax activation function is usually used to generate a probability distribution across the class labels for classification tasks.

VGG-16

Thirteen convolutional layers, five max-pooling layers, and three fully connected layers make up the 16-layer VGG-16 deep convolutional neural network architecture.

The network's architecture is designed as follows:

- Convolutional Layers: The first two layers are convolutional, each using 64 filters of size 3x3. This results in an input volume of 224x224x64
- Pooling Layers: A max-pooling layer with a 2x2 size and a stride of 2 is applied after the first convolutional layers, reducing the dimensions from 224x224x64 to 112x112x64
- Subsequent Convolutional Layers: The volume size is changed to 112x112x128 after applying two further convolutional layers, each of which has 128 filters of size 3x3. Following the application of a max-pooling layer, the dimensions are reduced to 56x56x128
- Convolutional Layers: The network has two further convolutional layers with 256 3x3 filters each, making the total volume size 28x28x256. Another max-pooling layer follows, reducing the size to 14x14x256
- Final Convolutional and Pooling Layers: The volume is subsequently processed by two more convolutional layers, each with 512 filters, and max-pooling reduces it to 7x7x512
- Fully Connected Layers: Three fully connected layers are applied to the flattened 7x7x512 volume before a softmax layer is applied to divide the output into three classes

The architecture of VGG-16 is shown in Figure 7, which also shows how the volume's proportions alter as it moves through the various tiers.

Fig. 7: VGG-16 Architecture

Algorithm steps for the proposed VGG16 model for paddy disease classification:

1. Input: Videos to frames
2. Output: Paddy Disease Classification
3. Upload the dataset
4. Import required libraries
5. Upload train and valid path
6. Initialize with weights of the VGG16 model
7. Resize the images to a fixed size of 224x224
8. Define Batch Size, Image Shape
9. Divide the dataset into two parts: testing and training
10. Set aside 20% for testing and 80% for training
11. Give the dense layer the data

DOI: 10.3844/jcssp.2025.1772.1784

12. Compile the model
13. Visualize the training/validation data
14. Test your model

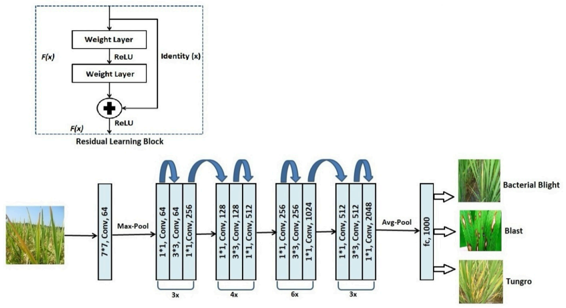

Fig. 8: ResNet50 Architecture for Paddy Classification

ResNet50

Researchers at Microsoft Research first proposed ResNet50 in 2015 and introduced the residual network architecture, a new design. The network's performance decreases or becomes saturated as it gets deeper. Since gradients are vanishing, accuracy is reduced. The idea of a residual network provides a solution to vanishing gradients during backpropagation. Skip connections are a method used by residual networks. A skip connection bypasses a few training steps and connects directly to the output. Gradients can pass directly from later levels to starting layers through the skip connections, as shown in Figure 8. A strong model that is frequently applied to a variety of computer vision problems is ResNet50. In order to lessen the vanishing gradient issue, skip connections are used, which add the output of one layer to the subsequent layer. It contains two blocks: an identity block and a convolution block. If the output and input are the same, then an identity block is used, and if the output is not equal to the input, then the convolution block is inserted so that the input will be equal to the output. An identity block is a type of residual block where the shortcut connection (skip connection) simply passes the input tensor (identity) directly to the output without any modifications. Identity blocks are used when the residual block's input and output dimensions are same. A convolutional block is a type of residual block used when the block's dimensions for input and output are different. Convolutional blocks are designed to adapt the spatial dimensions to match the desired output dimensions.

The ResNet 50 architecture contains the following elements:

- Initial Layers: 3×3 max pooling with stride 2, 7×7 convolution with 64 filters
- Residual Blocks
  - Conv2_x: 3 blocks with: 1×1, 3×3, 1×1 convolutions (64, 64, 256 filters)
  - Conv3_x: 4 blocks with: 1×1, 3×3, 1×1 convolutions (128, 128, 512 filters)
  - Conv4_x:6 blocks with: 1×1, 3×3, 1×1 convolutions (256, 256, 1024 filters)
  - Conv5_x:3 blocks with: 1×1, 3×3, 1×1 convolutions (512, 512, 2048 filters)
- Final Layers: Global average pooling, Fully connected layer for classification and the last layer contains three classes with a softmax activation function.

VGG-19

The design of VGG-19 is shown in Figure 9, which also shows how the volume dimensions change when the layers are added.

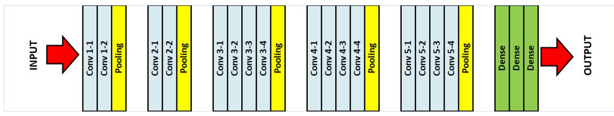

Fig. 9: Architecture of VGG-19

Input Layer:The network receives a fixed-size (224x224x3) picture as input.

Convolutional and Pooling Layers:

Block 1:

- Two convolutional layers with 64 3x3 filters
- The maximum pooling layer (2x2)

Block 2:

- Two convolutional layers with 128 3x3 filters
- The maximum pooling layer (2x2)

Block 3:

- Four convolutional layers with 256 3x3 filters
- The maximum pooling layer (2x2)

Block 4:

- Four convolutional layers with 512 3x3 filters
- The maximum pooling layer (2x2)

Block 5:

- Four convolutional layers with 512 3x3 filters
- The maximum pooling layer (2x2)

Fully Interconnected Layers*:*

- The final convolutional block's output is flattened
- It uses two completely connected layers with ReLU activation and 512 neurons, each
- The output layer, a final fully linked layer with three neurons and softmax activation, is employed

Results

Description of the Dataset

The dataset is collected using real time video of paddy diseases and then converted to images. All the RGB images are fed to the CNN, VGG16, VGG19 and ResNet50 models. Training and test sets have been created from the dataset. For "training" the architectures,

DOI: 10.3844/jcssp.2025.1772.1784

2296 paddy classification images are used, 575 paddy classification images are used for testing which is demonstrated in Table 1.

Table 1: Description of the Dataset

Paddy Disease	Training Images	Testing Images
Bacterial Blight	682	196
Blast	612	187
Tungro	1002	192
Total	2296	575

Paddy Disease Performance Using 2D-CNN

The 2D-CNN training and testing approach is covered in this section utilizing a real-time dataset with 8, 10, 12, and 14 layers. 3-Dimensional input data, batch size, filter size, number of filters, number of layers, and number of epochs are provided as input to the model, which is shown in Table 2.

Table 2: 2D-CNN with Layers 8, 10, 12, and 14 (Baljon, 2023)

	8 layers	10 layers	12 layers	14 layers
Input size	224x224x3	224x224x3	224x224x3	224x224x3
Conv 2D	224,224,32	224,224,32	224,224,32	224,224,32
Max-pooling 2D	112,112,32	112,112,32	112,112,32	112,112,32
Conv 1	112,112,64	112,112,64	112,112,64	112,112,64
Max-pooling 1	56,56,64	56,56,64	56,56,64	56,56,64
Conv 2	56,56,128	56,56,128	56,56,128	56,56,128
Max-pooling 2	28,28,128	28,28,128	28,28,128	28,28,128
Conv 3	28,28,256	28,28,256	28,28,256	28,28,256
Max-pooling 3	14,14,256	14,14,256	14,14,256	14,14,256
Conv 4		14,14,512	14,14,512	14,14,512
Max-pooling 4		7,7,512	7,7,512	7,7,512
Conv 5			7,7,512	7,7,512
Max-pooling 5			3,3,512	3,3,512
Conv 6				3,3,512
Max-pooling 6				1,1,512
Flatten	50176	25088	4608	512
Dense	(500)	(500)	(500)	500
Dense1	(250)	(250)	(250)	250
Dense2(SoftMax)	3 (753)			3
Trainable params	25,602,919	23,676,263	6,358,887	6,670,695

Performance of Paddy Disease Classification Using VGG-16

13 convolutional layers, five max-pooling layers, and three fully connected layers make up the 16 layers that make up VGG-16, as was previously indicated. The first convolutional layers' input dimensions are as follows:These dimensions are reduced to 112×112×64 by Max Pooling 1. Conv. Layer 1 and Conv. Layer 2 has a size of 224×224×64. The structure and measurements of each of the 16 layers are described in Table 3.

In this paper there are three paddy diseases, and the last layer i.e., in dense layer there are 3 classes shown in Table 4.

Table 3: VGG-16 Network Parameters

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 224, 224, 64)	1792
conv2d_2 (Conv2D)	(None, 224, 224, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 112, 112, 64)	0
conv2d_3 (Conv2D)	(None, 112, 112, 128)	73856
conv2d_4 (Conv2D)	(None, 112, 112, 128)	147584
max_pooling2d_2 (MaxPooling2D)	(None, 56, 56, 128)	0
conv2d_5 (Conv2D)	(None, 56, 56, 256)	295168
conv2d_6 (Conv2D)	(None, 56, 56, 256)	590080
conv2d_7 (Conv2D)	(None, 56, 56, 256)	590080
max_pooling2d_3 (MaxPooling2D)	(None, 28, 28, 256)	0
conv2d_8 (Conv2D)	(None, 28, 28, 512)	1180160
conv2d_9 (Conv2D)	(None, 28, 28, 512)	2359808
conv2d_10 (Conv2D)	(None, 28, 28, 512)	2359808
max_pooling2d_4 (MaxPooling2D)	(None, 14, 14, 512)	0
conv2d_11 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_12 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_13 (Conv2D)	(None, 14, 14, 512)	2359808
max_pooling2d_5 (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_1 (Dense)	(None, 4096)	102764544
dropout_1 (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 4096)	16781312
dropout_2 (Dropout)	(None, 4096)	0
dense_3 (Dense)	(None, 2)	8194
Total params: 134,268,738		
Trainable params: 134,268,738		
Non-trainable params: 0		

Table 4: VGG16 Parameters with 3 Classes

Layer (type)	Units	Parameters
FC1 (Dense)	256	64,22,784
FC2 (Dense)	128	32,896
Softmax	3	387
Trainable parameters: 21,170,755		

Performance of Paddy Disease Classification with ResNet50

In this instance, the backpropagation technique is used. The deeper the network gets, the harder it is to converge. Convolutional layers with zero padding, max pooling, activation functions, batch normalization layers, average pooling, and fully linked layers make up the 50 layers that makeup ResNet-50, as was previously said. 224×224×64 is the input dimension for Conv. Layer 1, 224×224×64 is for Conv. Layer 2, and 55×55×64 is the result of Max Pooling 1. Table 5 provides specifics on the composition and size of the 50 layers.

DOI: 10.3844/jcssp.2025.1772.1784

Table 5: ResNet50 Network Parameters

Layer name	Output size	50-layer
conv1	112×112	7×7, 64, stride 2
conv2.x	56×56	3×3 max pool, stride 2
		[1×1,64 3×3,64 1×1,256]×3
conv3.x	28×28	[1×1,128 3×3,128 1×1,512]×4
conv4.x	14×14	[1×1,256 3×3,256 1×1,1024]×6
conv5.x	7×7	[1×1,512 3×3,512 1×1,2048]×3
	1×1	average pool, 3 fc, softmax

Table 6: Performance Metrics Formulas

Accuracy	Precision	Recall	F-score
$\frac{TP+TN}{TP+TN+FP+FN}$	$\frac{TP}{TP+FP}$	$\frac{TP}{TP+FN}$	$\frac{2\times P\times R}{P+R}$

Performance Analysis

Evaluating the trained models involves key stages of training and testing to gauge performance. For this case, 2,296 samples are processed by the trained 2D-CNN model. A confusion matrix, a useful tool for evaluating metrics like True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN), and Accuracy (ACC), is used to summarize the results. Both binary and multi-class classification problems benefit greatly from this approach.

True Positive (TP): Predicting a label as the positive class with accuracy.

True Negative (TN): Predicting a label as the negative class with accuracy.

False Positive (FP): When a label is incorrectly predicted to be the positive class when it should be the negative class.

False Negative (FN): When a label is mistakenly predicted to be the negative class when it should be the positive one.

The F-score, which is the harmonic mean of Precision (P) and Recall (R), is the result of combining precision and recall. Table 6 shows the performance analysis for moving object detection using the suggested method. Table 7 displays the 2D CNN's performance with various layers. The performance of VGG-16, VGG-19, and ResNet-50 is shown in Table 8, and Figure 10 provides a graphic representation of the findings.

Table 7: Comparison of Paddy Disease Classification Performance with Real-Time Datasets Using 2D-CNN

Paddy Disease	8 Layers			10 Layers			12 Layers			14 Layers		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Bacterial blight	0.99	0.95	0.97	0.99	0.94	0.97	0.72	1.00	0.84	0.77	1.00	0.87
Blast	0.88	0.98	0.93	0.88	0.93	0.90	1.00	0.15	0.26	1.00	0.08	0.14
Tungro	1.00	0.99	1.00	0.99	1.00	0.99	0.99	1.00	0.99	0.98	1.00	0.99

Table 8: Comparative Effectiveness of VGG16, VGG19, and ResNet50 in the Classification of Paddy Disease Using Real-Time Data

Paddy Disease	VGG16			VGG19			ResNet50		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
Bacterial blight	0.96	0.90	0.93	0.95	0.97	0.96	0.99	0.97	0.98
Blast	0.76	0.89	0.80	0.88	0.91	0.89	0.99	0.93	0.97
Tungro	0.94	0.91	0.92	0.98	0.95	0.97	0.98	0.99	0.99

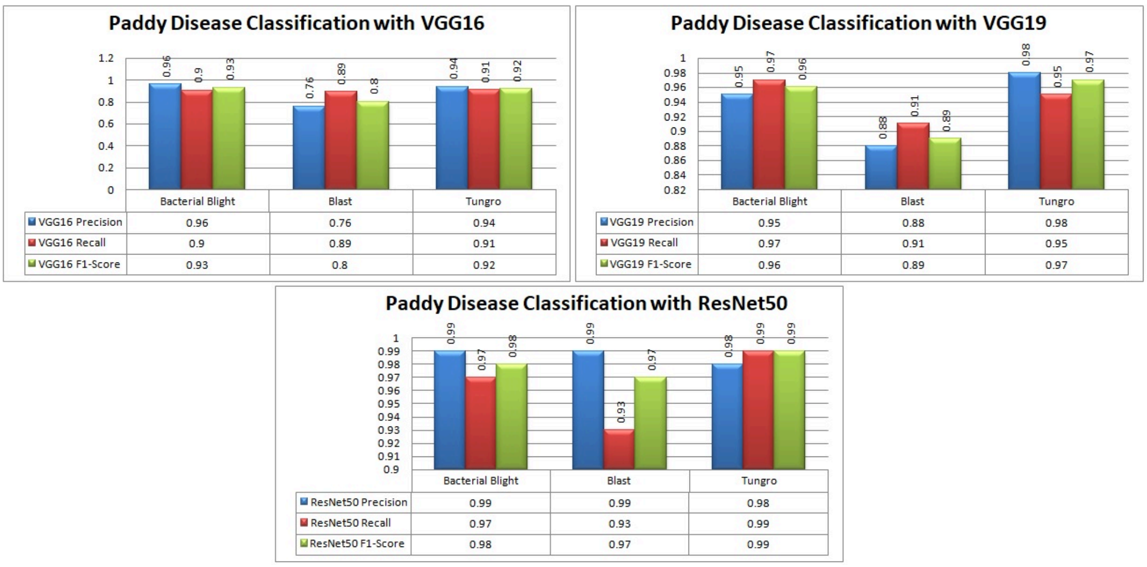

Fig. 10: Performance of Paddy Disease Classification for Real-Time Dataset Using VGG16, VGG19 and ResNet50 of Different Evaluation Metrics

Overall performance of four models is shown in Table 9 and graphically shown in Figure 11 and comparison with existing methods is shown in Table 10.

Table 9: Overall Performance of Paddy Disease Classification Accuracy with Real-Time Dataset Using 2D-CNN, VGG16, VGG19and ResNet50

Model	Accuracy
2D-CNN	96.73%
VGG16	93.23%
VGG19	95.35%
ResNet50	99.43%

The 2D-CNN model trained with 8 convolutional layers outperforms models with 10, 12, and 14 convolutional layers for different numbers of convolutional layers. According to Table 9, the ResNet-50 model performs better than the other models, including 2D-CNN, VGG-19, and VGG-16.

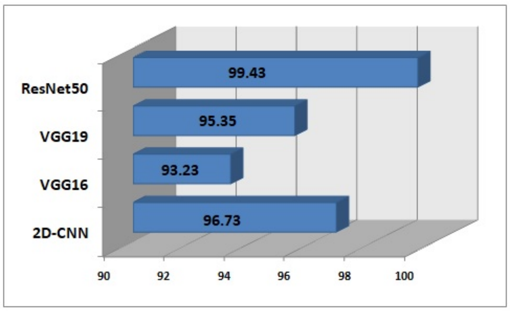

Fig. 11: Overall Performance of Paddy Disease Classification for Real-Time Dataset Using 2D-CNN, VGG16, VGG19, ResNet50

Table 10: Comparison of the Real-Time Paddy Disease Classification Performance with Existing Work Using 2D-CNN, VGG16, VGG19, and ResNet50

Existing Methods	Methods	Accuracy
Swathika *et al.* (2021)	CNN	70.00%
Debnath and Saha (2022)	CNN, IOT	97.70%
Pal (2021)	Inception V2, GoogleNet	96.43%
Proposed Method	2D-CNN	96.73%
	VGG16	93.23%
	VGG19	95.35%
	ResNet50	99.43%

Discussion

This work used deep learning techniques to suggest a new and reliable method for classifying illnesses of rice crops. The construction and assessment of unique 2D CNN architectures with different depths, specifically 8, 10, 12, and 14 layers is a significant breakthrough in this work. The 10-layer CNN outperformed the others, showing a good trade-off between classification accuracy and model complexity. In contrast to many previous studies that rely on fixed or generic models, this layered experimentation makes a novel contribution by methodically identifying an ideal architecture adapted for agricultural picture data.

Standard pretrained models like VGG16, VGG19, and ResNet50 were also used in addition to the CNN. With a classification accuracy of 99.43%, ResNet50 fared better than any other model evaluated, demonstrating its superior feature extraction capabilities through residual learning. However, the competitive performance of the customized 10 layer CNN highlights the promise of lightweight, domain-specific models, especially in situations when computational efficiency is crucial.

A practical and field-oriented approach was employed to gather the dataset for this study: recordings were taken straight from the Karimnagar District's paddy fields, and they were then transformed into image frames to produce the training and testing datasets. A varied and realistic dataset reflecting real-world field settings, including changes in lighting, angles, and organic backdrop features, was produced using this method. Resizing and normalization were the only preprocessing techniques used on these photos, however they were efficient in guaranteeing consistent input dimensions and steady model convergence.

The trained models' suitability for field deployment is increased by simulating real-world use-case situations through real-world data collecting and minimum preparation. The findings demonstrate that deep learning models can be extremely accurate and scalable crop disease control tools, especially when they are optimized or created using domain-specific datasets.

Integrating these models with IoT devices for real-time disease monitoring and alarms may be the main focus of future research. The precision of ResNet50 and the lightweight construction of the suitable CNN make them appropriate for edge computing applications, including embedded systems in agricultural settings or drones or smartphones.

Conclusion

This paper proposed the paddy crop disease classification systems by using CNN, VGG19, ResNet50 and VGG16 models and the accuracies are better as compared to some previous works. The accuracy of the ResNet-50 method was 99.43%, better than CNN, VGG-16, and VGG-19. These methods will be combined for real-time use in agricultural fields in the future when this work is used to develop IoT-based applications.

Acknowledgment

The authors are thankful to Dr. M. Sowmya, Asst. Professor in CSE Department, Stanley College of Engineering and Technology for Women, Hyderabad, India, for her valuable inputs in the AI domain and Mr K. Radhakishan, JTO, BSNL Telangana Circle, India, for his support in providing real-time paddy crop at Gopalpur Village, Karimnagar District, Telangana, India.

Funding Information

This work was carried out without any external financial assistance.

Author's Contributions

Shiva Shankar J: Instrumental in the conceptualization, real-time data collection and analysis.

S. Palanivel: Significantly contributed to the thorough analysis and evaluation.

S. China Venkateswarlu: Played a pivotal role in the concept design and real-time data collection.

All authors contributed greatly towards the analysis of real-time data and preparation of the manuscript.

Ethics

There are no ethical issues to be concerned with in connection with this manuscript.

References

Anuar, M. M., Halin, A. A., Perumal, T., & Kalantar, B. (2022). Aerial Imagery Paddy Seedlings Inspection Using Deep Learning. *Remote Sensing*, *14*(2), 274. https://doi.org/10.3390/rs14020274

Attallah, O. (2023). RiPa-Net: Recognition of Rice Paddy Diseases with Duo-Layers of CNNs Fostered by Feature Transformation and Selection. *Biomimetics*, *8*(5), 417. https://doi.org/10.3390/biomimetics8050417

Baljon, M. (2023). A Framework for Agriculture Plant Disease Prediction Using Deep Learning Classifier. *International Journal of Advanced Computer Science and Applications*, *14*(8), 1098-1111. https://doi.org/10.14569/ijacsa.2023.01408119

Bi, X., & Wang, H. (2024). Double-Branch Deep Convolutional Neural Network-Based Rice Leaf Diseases Recognition and Classification. *Journal of Agricultural Engineering*, *55*(1), 1544. https://doi.org/10.4081/jae.2023.1544

Debnath, O., & Saha, H. N. (2022). An IoT-Based Intelligent Farming Using CNN for Early Disease Detection in Rice Paddy. *Microprocessors and Microsystems*, *94*, 104631. https://doi.org/10.1016/j.micpro.2022.104631

Dhiman, A., & Saroha, V. (2022). Detection of Severity of Disease in Paddy Leaf by Integrating Edge Detection to CNN-Based Model. *2022 9th International Conference on Computing for Sustainable Global Development (INDIACom)*, 470-475. https://doi.org/10.23919/indiacom54597.2022.9763128

Hasan, Md. M., Rahman, T., Uddin, A. F. M. S., Galib, S. Md., Akhond, M. R., Uddin, Md. J., & Hossain, Md. A. (2023). Enhancing Rice Crop Management: Disease Classification Using Convolutional Neural Networks and Mobile Application Integration. *Agriculture*, *13*(8), 1549. https://doi.org/10.3390/agriculture13081549

Hossain, K. A., Raihan, M., Biswas, A., Sarkar, J. P., Sultana, S., Sana, K., Sarder, K., & Majumder, N. (2022). Paddy Disease Prediction Using Convolutional Neural Network. *Lecture Notes in Networks and Systems*, *371*, 268-276. https://doi.org/10.1007/978-3-030-93247-3_27

Imrankhan, M., Arunachalam, V., Dhanush, S. K., & Yugendran, V. (2024). Detection and Prevention of Rice Leaf Disease Using DCNN_ Resnet50 Technique. *African Journal of Biological Sciences*, *6*(Si2), 612-621. https://doi.org/10.33472/AFJBS.6.Si2.2024.612-62

Iparraguirre-Villanueva, O., Guevara-Ponce, V., Torres-Ceclén, C., Ruiz-Alvarado, J., Castro-Leon, G., Roque-Paredes, O., Zapata-Paulini, J., & Cabanillas-Carbonell, M. (2023). Disease Identification in Crop Plants Based on Convolutional Neural Networks. *International Journal of Advanced Computer Science and Applications*, *14*(3), 519-528. https://doi.org/10.14569/ijacsa.2023.0140360

Malvade, N. N., Yakkundimath, R., Saunshi, G., Elemmi, M. C., & Baraki, P. (2022). A Comparative Analysis of Paddy Crop Biotic Stress Classification Using Pre-Trained Deep Neural Networks. *Artificial Intelligence in Agriculture*, *6*, 167-175. https://doi.org/10.1016/j.aiia.2022.09.001

Mogilicharla, S., & Mummadi, U. K. (2024). Enhanced Rice Plant Disease Identification: A Hybrid Approach of Transfer Learning, SVM and PCA. *Journal of Theoretical and Applied Information Technology*, *102*(9), 4164-4179.

Narmadha, R. P., Sengottaiyan, N., & Kavitha, R. J. (2022). Deep Transfer Learning Based Rice Plant Disease Detection Model. *Intelligent Automation and Soft Computing*, *31*(2), 1257-1271. https://doi.org/10.32604/iasc.2022.020679

Pal, O. K. (2021). Identification of Paddy Leaf Diseases Using a Supervised Neural Network. *2021 16th International Conference on Emerging Technologies (ICET)*, 1-4. https://doi.org/10.1109/icet54505.2021.9689788

Purbasari, I. Y., Rahmat, B., & Putra PN, C. S. (2021). Detection of Rice Plant Diseases using Convolutional Neural Network. *IOP Conference Series: Materials Science and Engineering*, *1125*, 012021. https://doi.org/10.1088/1757-899x/1125/1/012021

Quy Thanh, L. (2023). An Approach for Classification of Diseases on Leaves. *International Journal of Advanced Computer Science and Applications*, *14*(10), 1065-1071. https://doi.org/10.14569/IJACSA.2023.01410112

Suseno, J. R. K., Minarno, A. E., & Azhar, Y. (2023). The Implementation of Pretrained VGG16 Model for Rice Leaf Disease Classification Using Image Segmentation. *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control*, *8*(1), 499-506. https://doi.org/10.22219/kinetik.v8i1.1592

Swathika, R., Srinidhi., S., Radha, N., & Sowmya., K. (2021). Disease Identification in Paddy Leaves Using CNN Based Deep Learning. *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, 1004-1008. https://doi.org/10.1109/icicv50876.2021.9388557

Taujuddin, N. S. A. M., Halim, N. H. N. A., Norsuha, M. S., Koogeethavani, R., Husin, Z. H., Ghani, A. R. A., & Qadir, T. O. (2021). Brown Spot Disease Severity Level Detection Using Binary-RGB Image Masking. *International Journal of Advanced Computer Science and Applications*, *12*(9), 548-553. https://doi.org/10.14569/ijacsa.2021.0120962

Thamarai, S. S. B., Thirumurugan, S., Kanish, P., & Surya, M. (2024). Deep Learning Based Paddy Disease Classification Using Resnet-50. *Proceedings of the 1st International Conference on Artificial Intelligence, Communication, IoT, Data Engineering and Security, IACIDS 2023, 23-25 November 2023, Lavasa, Pune, India*. Proceedings of the 1st International Conference on Artificial Intelligence, Communication, IoT, Data Engineering and Security, IACIDS 2023, 23-25 November 2023, Lavasa, Pune, India, Lavasa, India. https://doi.org/10.4108/eai.23-11-2023.2343203

Thomkaew, J., & Intakosum, S. (2022). Improvement Classification Approach in Tomato Leaf Disease Using Modified Visual Geometry Group (VGG)-InceptionV3. *International Journal of Advanced Computer Science and Applications*, *13*(12), 362-370. https://doi.org/10.14569/ijacsa.2022.0131244

Vamsee Kongara, R. K., Siva Charan Somasila, V., Revanth, N., & Polagani, R. D. (2022). Classification and Comparison Study of Rice Plant Diseases Using Pre-Trained CNN Models. *2022 International Conference on Inventive Computation Technologies (ICICT)*, 140-145. https://doi.org/10.1109/icict54344.2022.9850784

Vignesh, U., & Elakya, R. (2022). Identification of Unhealthy Leaves in Paddy by Using Computer Vision Based Deep Learning Model. *International Journal of Electrical and Electronics Research*, *10*(4), 796-800. https://doi.org/10.37391/ijeer.100405

Zainorzuli, S. M. (2023). *Comparison Between Alexnet, Googlenet and ResNet-50 for Brownspot, Hispa and Leafblast Disease Classification*.

Zaki, M. A., Narejo, S., Ahsan, M., Zai, S., Anjum, M. R., & Din, N. u. (2021). Image-Based Onion Disease (Purple Blotch) Detection using Deep Convolutional Neural Network. *International Journal of Advanced Computer Science and Applications*, *12*(5), 448-458. https://doi.org/10.14569/ijacsa.2021.0120556

Zhang, X., Dong, H., Gong, L., Cheng, X., Ge, Z., & Guo, L. (2023). Multiple paddy disease recognition methods based on deformable transformer attention mechanism in complex scenarios. *International Journal of Computers and Applications*, *45*(10), 660-672. https://doi.org/10.1080/1206212x.2023.2263254