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Research Article

Deep Learning based Rice Plant Disease detection and classification using Densely Convolution Neural Network (DenseNet) with Multi-Layer Perceptron (MLP)

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ABSTRACT

Rice is a staple food crop for more than half of the world's population, playing a crucial role in global food security. However, the cultivation of rice is frequently threatened by a range of diseases, ranging which can negatively affect food supply chains and result in large yield losses. In order to ensure sustainable development of rice and secure food resources, it is crucial to understand and deal with rice plant diseases. Rice plant diseases can be broadly classified into fungal, bacterial, viral, and nematode diseases. Among these, fungal diseases are the most prevalent and destructive, with rice blast, sheath blight, and brown spot being particularly notorious. In recent years, the rapid advancements in deep learning have opened new avenues for addressing complex problems in various domains. This paper introduces a novel deep learning-based model for the detection and classification of Rice Plant Disease (RPD) using a combination of Densely Convolutional Neural Network (DenseNet) and Multi-Layer Perceptron (MLP), termed the DenseNet-169-MLP model. The input consisted of pictures of afflicted rice leaves on a white backdrop. Following the required preprocessing and cleaning of the collected data which may involve fixing missing values, harmonizing the data format, as well as getting rid of noise. Find pertinent characteristics in the dataset that can be used to distinguish between various illnesses. This involves techniques such as image processing to extract features from images of affected rice plants. Based on the anticipated disease class, group rice diseases into several categories. This can help with identifying disease trends, putting suitable management plans into place, and giving farmers focused advice. A variety of Deep Learning techniques were used to train the dataset including AlexNet,VGG16 and DenseNet-169-MLP. DenseNet-169-MLP achieved an accuracy of 94.05 when applied on the Rice plant disease dataset.

Keywords:Rice Plant Disease(RPD), Densely Convolutional Neural Network , Multi-Layer Perceptron(MLP) , Visual Geometry Group-16(VGG19).

INTRODUCTION

Rice is a staple food in India and a crucial part of the country's agriculture and economy. It is the primary source of livelihood for millions of farmers and a fundamental component of the Indian diet.Rice is grown in almost all states of India, with significant cultivation in the eastern, southern, and northeastern regions. Major rice-producing states include West Bengal, Uttar Pradesh, Punjab, Bihar, Odisha, Andhra Pradesh, Telangana, Tamil Nadu, Karnataka, and Assam.Rice cultivation in India is predominantly rain-fed and depends heavily on the monsoon season. The crop thrives in warm and humid climates, requiring temperatures between 20°C to 37°C and annual rainfall between 1000 to 1500 mm. The Kharif season (June to November) is the primary rice-growing season, coinciding with the southwest monsoon. In some areas, rice is also grown during the Rabi season (November to April) under irrigated conditions.Rice can be grown on a variety of soils, including loamy, silty, and clayey soils. However, fertile alluvial soils with good water retention capacity are considered ideal. Proper field preparation, including puddling

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and leveling, is essential for successful rice cultivation.Rice Plant Disease could greatly reduce the yields. Mainly, the disease is occurred by fungi, bacteria, or viruses. The general disease of Rice Plants includes Bacterial Leaf Blight(BLB),Brown Spot(BS) and Leaf Smut(LS).

Fig-1 (a)Bacterial Blight (b)Brown Spot and (c)Leaf Smut

Bacterial Leaf Blight (BLB)

Bacterial leaf blight (BLB) in rice, caused by the bacterium *Xanthomonas oryzae*pv. *oryzae*, is a severe disease that leads to significant yield losses. Early symptoms include water-soaked streaks on leaf margins and tips, which progress to yellow and then brown lesions. In young seedlings, systemic infection can cause a condition known as kresek, characterized by rolled, pale green leaves and plant death. BLB thrives in warm, humid conditions, particularly with temperatures between 25-34°C and high humidity, and it is exacerbated by heavy rainfall, flooding, and dense planting. Management strategies include using resistant rice varieties, certified disease-free seeds, proper water management, field sanitation, and preventive application of copper-based bactericides.

Brown Spot (BS)

Brown spot, caused by the fungus *Bipolarisoryzae*, is a common fungal disease of rice that affects leaves, seedlings, and grains. The disease manifests as small, circular to oval, dark brown lesions with gray or light brown centers on the leaves. Infected seedlings exhibit reduced vigor and stunting, while grains develop reddish-brown discoloration, affecting quality. Brown spot is more prevalent in warm, moist conditions and in fields with poor soil fertility or drought stress. Management involves ensuring balanced soil nutrition, particularly adequate nitrogen, practicing crop rotation, using resistant varieties, maintaining field sanitation, and applying fungicides such as mancozeb, thiophanate-methyl, or propiconazole at early stages of infection.

Leaf Smut (LS)

Leaf smut, caused by the fungus *Entylomaoryzae*, is a disease characterized by black, elongated smut sori on the upper leaf surface and leaf sheaths of rice plants. These sori are slightly raised and release dark spores upon rupturing. The disease thrives in warm and humid conditions and is more prevalent in plants under stress, such as nutrient deficiencies or water stress. Management of leaf smut primarily involves the use of resistant varieties, maintaining good plant health through balanced fertilization and adequate water management, and removing infected plant debris to reduce inoculum levels. Chemical control is generally not recommended, as leaf smut typically does not cause significant yield loss.

Machine learning can be utilized for rice plant disease diagnosis and classification to improve accuracy and efficiency. Here's an overview of the process:

Data collection: Gather a comprehensive dataset containing information about various rice diseases, including symptoms, causal agents, and other relevant characteristics.

Data preprocessing: Clean and preprocess the collected data, which may involve removing noise, handling missing values, and standardizing the data format.

Feature extraction: Identify relevant features from the dataset that can effectively differentiate between different diseases. This may involve techniques such as image processing to extract features from images of affected rice plants.

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Model training: Utilize machine learning algorithms, such as decision trees, support vector machines, or deep learning models, to train a classification model using the preprocessed data. The model learns patterns and relationships between the input features and disease classes.

Model evaluation: Assess the performance of the trained model using evaluation metrics such as accuracy, precision, recall, and F1 score. Cross-validation techniques can be employed to ensure the model's generalizability.

Disease diagnosis: Apply the trained model to new, unseen data, such as images or symptom descriptions of potentially infected rice plants, to predict the most likely disease class.

Disease classification: Classify rice diseases into different categories based on the predicted disease class. This can aid in understanding disease patterns, implementing appropriate management strategies, and providing targeted recommendations to farmers.

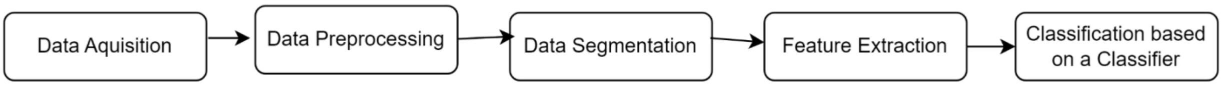

fig-2 An overview of diagnosis and classification

LITERATURE SURVEY

Latif et al.[1] has proposed a transfer learning-based method using Deep neural networks using convolution (DCNN) for precise rice leaf disease identification and classification. The recommended method uses a modified VGG19-based transfer learning model that can correctly identify and diagnose six distinct classes: microbial leaf blight, narrow brown identify leaf scald, leaf blast, and healthy. Using a non-normalized augmented dataset, the model achieved an average accuracy of 96.08%, with precision, recall, specificity, and F1-score of 0.9620, 0.9617, 0.9921, and 0.9616, respectively. This modified approach significantly outperforms similar methods using the same or comparable datasets reported in existing literature.Roopali Dogra et al.[2]addressed the issue of rice plant disease by employing Deep Learning (DL) and transfer learning techniques to accurately identify and classify rice leaf diseases. A comprehensive dataset of 5932 self-generated rice leaf images, along with benchmark datasets, was categorized into nine classes, including healthy, mild and severe blight, tungro, blast, and brown spot. Meticulously labeled and validated by horticulture experts, the dataset was augmented to increase image numbers. Tailored Convolutional Neural Network models were evaluated against alternative transfer learning approaches like VGG16, Xception, ResNet50, DenseNet121, Inception ResNetV2, and Inception V3. The custom VGG16 model achieved an exceptional 99.94% accuracy, surpassing existing benchmarks, with interpretable AI visualizing layer-wise feature extraction.Convolutional Neural Networks (CNNs) are highly effective for image-based prediction problems due to minimal preprocessing requirements. This study reviews how Deep Learning (DL) aids in diagnosing and categorizing rice plant diseases, highlighting the superior performance of models like VGG16, VGG19, MobileNet-V2, LeNet5, and ResNet[3]. Notably, R-CNN models achieve accuracies of 96% for blast, 95% for brown spot, and 94.5% for sheath blight, making them highly suitable for detecting various rice plant diseases.

Shrivastava, V. K et al.[4] has used transfer learning with deep CNNs for classifying rice diseases, achieving a classification accuracy of 91.37% with an 80%-20% training-testing split. However, benchmarking against existing literature is challenging due to the lack of standard labeled rice disease images, and performance can be improved with a larger dataset.P. Isaac Ritharson et al[5] has experimented with the VGG16 model which demonstrated exceptional performance in identifying and categorizing nine rice leaf disease classes, obtaining high precision as well as recall scores, 99.94% accuracy, and providing a dependable approach to plant disease diagnosis. Based on factors including model and parameter size, six transfer models were chosen and retrained; VGG16 fared highly in terms of accuracy, precision, and recall. Through trial and error, the model was optimized through additional parameter fine-tuning, resulting in the addition of filters, substantial layers, and dropouts.

Mayuri Sharma et al[6] investigated the potential of various machine learning models for diagnosing rice diseases, including six diverse transfer learning architectures and comprehensive deep learning models. The study contrasts

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transfer learning's performance with that of traditional machine learning and associated research. The research studies use reinforcement approaches to enlarge the dataset and focus on three common diseases: rice brown spot, paddy blast, and bacterial blight. Studies indicate that when compared with standard machine learning models, InceptionResNetV2 (98.9%), Xception, which (97.65%), ResNet50 (97%), MobileNet (96.65%), and InceptionV3 (95.85%) produce greater rates of rice disease diagnosis. Hasan et al[7] presented an innovative approach to detecting rice diseases using AI and computer vision techniques. By combining an SVM classifier with a deep CNN model and employing transfer learning, the model was retrained on 1080 images of nine different rice diseases. The SVM classifier, trained with features extracted from the DCNN model, achieved a 97.5% accuracy in identifying and classifying the diseases.Hassan S.M et al[8] suggested a new deep learning model that uses depth-wise separable convolution to decrease parameters and is based on the beginning layer and residual connections. The model was trained and tested on three plant disease datasets, achieving 99.39% accuracy on PlantVillage, 99.66% on rice disease, and 76.59% on cassava. Despite fewer parameters, it outperforms state-of-the-art deep learning models in accuracy.

Vasantha et al[9] highlights recent and superior solutions, finding that a CNN model with high-level fusion achieves perfect test accuracy (1.0) for three common rice plant diseases: Leaf Smut (LS), Bacterial Leaf Blight (BLB), and Brown Spot (BS). AlexNet with a neural network, achieving 0.99 accuracy, is the second-best method, while a deep feature-based SVM method shows superior F1 score and accuracy compared to other methods. Kumar, V. S et al[10] hasproposed and evaluated a precise method for detecting rice leaf diseases using the DenseNet-Bi-FAPN with YOLOv5 model on the Rice Leaf Disease (RLD) dataset. The YOLOv5 network enhances detection accuracy by integrating DAIS segmentation and Bi-FAPN networks, achieving 94.87% accuracy and 91.89% efficiency, outperforming methods like Faster-RCNN, Mask RCNN, RPN, YOLOv3, YOLOv4, and YOLOv5. The computational cost is reduced using a principled pruning approach. Singh, S. P et al.[11] presented a custom CNN-based architecture for detecting and classifying rice plant diseases. Initially tested on four diseased classes, both Stochastic Gradient Descent with Momentum (SGDM) and Adam-based models achieved over 99% accuracy with no significant performance difference. When including a healthy leaf dataset, the Adam-based model outperformed the SGDM-based model, achieving accuracies of 99.66% and 97.61% respectively. This inclusion enables the model to distinguish between healthy and diseased leaves, facilitating the detection of disease-free plants

PROPOSED METHODOLOGY

Fig-3 proposed architecture.

ALEXNET

ALEXNET isa convolutional neural network (CNN) architecture that has proven to be effective in detecting diseases in rice plants. The process begins with the collection of a comprehensive dataset comprising images of healthy and diseased rice plants, covering a range of disease types. These images undergo preprocessing to ensure uniformity in size and color, and sometimes data augmentation is applied to enhance the dataset's diversity. The AlexNet model, known for its deep learning capabilities, is then trained on these images. AlexNet's architecture, with multiple convolutional layers followed by fully connected layers, excels in extracting and learning the features

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needed to distinguish between healthy and diseased plants. The dataset is typically divided into training, validation, and test sets to rigorously evaluate the model's performance using metrics like accuracy, precision, recall, and F1-score. Fine-tuning the model, often through transfer learning using a pretrained AlexNet on a large dataset like ImageNet, can significantly boost its accuracy.

VGG16

The **VGG16**, a deep convolutional neural network (CNN) architecture, is highly effective in detecting rice plant diseases. The process starts with assembling a comprehensive dataset of images depicting healthy and diseased rice plants, encompassing a variety of disease types. These images are preprocessed to ensure uniformity in size and color, and data augmentation techniques are often employed to enhance the dataset's diversity. The VGG16 model, characterized by its depth and simplicity with 16 weight layers, is then trained on this dataset. VGG16's architecture, consisting of multiple convolutional layers followed by fully connected layers, is adept at extracting intricate features necessary for distinguishing between healthy and diseased plants. The dataset is typically divided into training, validation, and test sets, allowing for rigorous performance evaluation through metrics such as accuracy, precision, recall, and F1-score. Fine-tuning the model, often involving transfer learning with a pretrained VGG16 on a large dataset like ImageNet, can significantly improve its accuracy and efficiency.

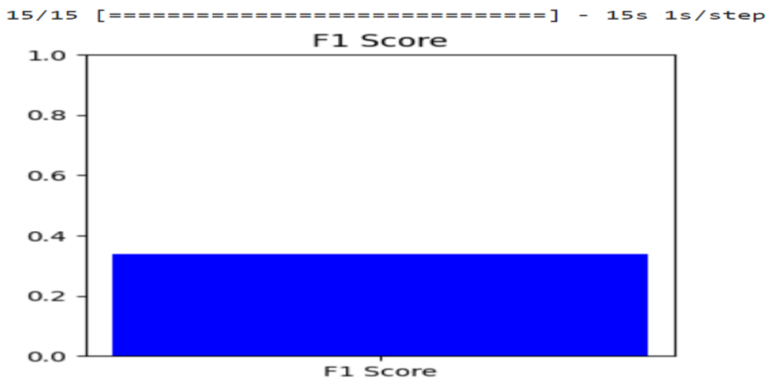
DenseNet-169

The **DenseNet-169**, a powerful convolutional neural network (CNN) architecture, is highly effective for detecting rice plant diseases. The process begins with collecting a comprehensive dataset of images showing both healthy and diseased rice plants, covering various disease types. These images are preprocessed to ensure consistency in size and color, and data augmentation is often applied to increase the dataset's diversity. DenseNet-169, known for its dense connectivity pattern where each layer receives input from all previous layers, is then trained on this dataset. This architecture enhances feature propagation and reduces the number of parameters, making it highly efficient at learning complex features necessary for distinguishing between healthy and diseased plants. The dataset is typically split into training, validation, and test sets to rigorously evaluate the model's performance using metrics such as accuracy, precision, recall, and F1-score. Fine-tuning the model, often through The accuracy of a pretrained DenseNet-169 can be substantially boosted by transfer learning on a big dataset, such as ImageNet. Once the model behaves satisfactorily, it can be used in real-world scenarios, including drone-based systems or smartphone apps, to facilitate real-time disease detection in rice fields. This technological advancement helps farmers achieve early and accurate disease management, ultimately contributing to better crop health and yield.

Dataset Description:

The sample images collected in this paper were collected from Open Source Kaggle which offers a vast repository of datasets from which we have chosen Rice plant disease dataset which consists of 4684 images of 3 types such as Bacterial Blight with a collection of 1604 images,Brown Spot with a collection of 1620 images and Leaf Blast with a collection of 1460 images.fig-1 shows the sample images of Dataset

RESULTS AND DISCUSSION



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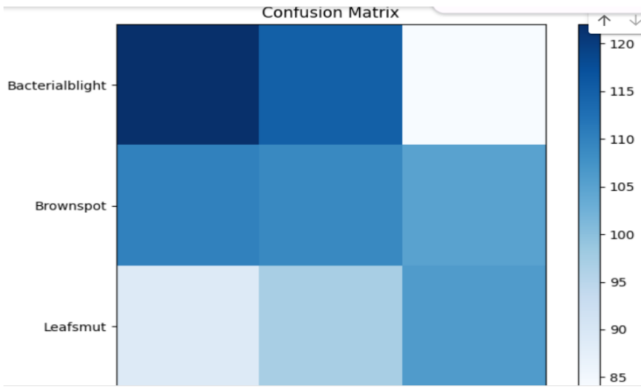

Fig-4 a) F1 score b) confusion matrix

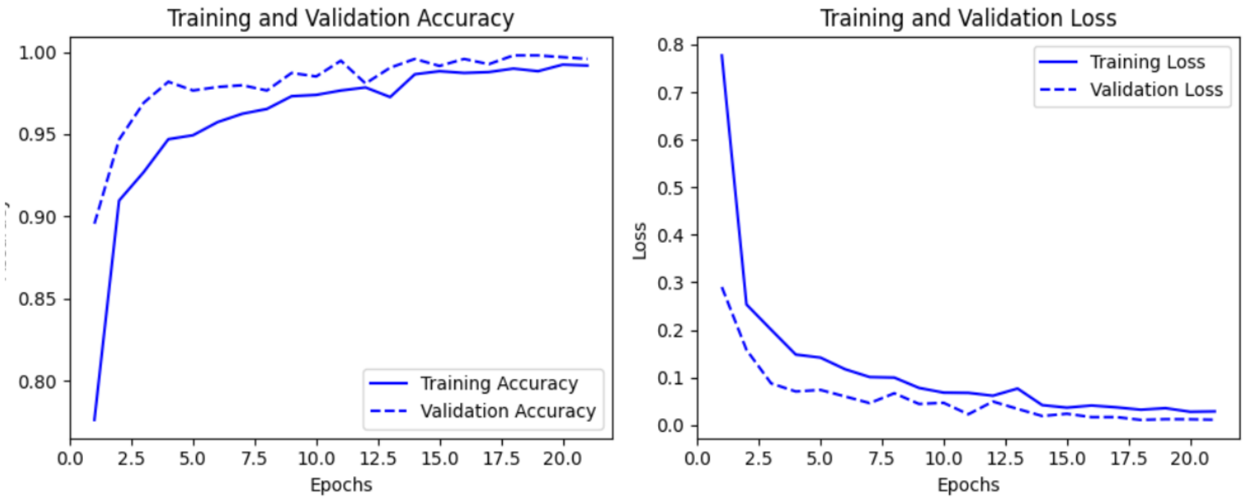

Fig-5 a) model accuracy and b) model loss

The above fig-5 contains two line plots that visualize the performance of a machine learning model over 20 epochs. The left plot represents the training and validation accuracy, while the right plot displays the training and validation loss. In the accuracy plot, the x-axis denotes the number of epochs, and the y-axis represents accuracy, ranging from approximately 0.75 to 1.00. The solid blue line corresponds to the training accuracy, while the dashed blue line represents the validation accuracy. Initially, both accuracies increase sharply, with validation accuracy slightly fluctuating. Over time, training accuracy reaches nearly 100%, and validation accuracy remains close, indicating that the model generalizes well without significant overfitting. In the loss plot, the x-axis again represents epochs, while the y-axis denotes loss values ranging from 0 to 0.8. The solid blue line shows the training loss, and the dashed blue line indicates the validation loss. Both loss values decrease rapidly in the first few epochs, demonstrating effective learning. As training progresses, the losses stabilize near zero, and there is no significant divergence between training and validation loss, which suggests that the model is not overfitting. If overfitting were occurring, the validation loss would increase while training loss continued decreasing, but that is not the case here. The overall trend in both plots suggests that the model is well-trained, achieving high accuracy with minimal loss. However, further evaluation using test data would be necessary to confirm its generalization capability beyond the validation set.

CONCLUSION

Rice, as a staple food crop for a significant portion of the world's population, faces considerable threats from various diseases, especially fungal ones like rice blast, sheath blight, and brown spot, which pose challenges to global food security. This paper presented a novel deep learning-based approach, the DenseNet-169-MLP model, for effective detection and classification of rice plant diseases. By leveraging advanced Techniques associated with

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image processing and a robust combination of DenseNet and MLP, the model achieved a remarkable accuracy of 94.05% on the Rice Plant Disease dataset. Such advancements highlight the potential of deep learning in providing precise and efficient disease identification, enabling better disease management strategies, and empowering farmers with actionable insights to safeguard rice production and ensure food sustainability.

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