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Botanicvision: CNN Driven Rice Leaf Disease Detection

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Abstract— This research addresses a pressing concern in the field of rice plant agriculture by developing a CNN model for the detection and recognition of Bacterial leaf blight, Tungro, Brown Spot, Leaf Blast, Leaf Smut. Traditional methods of disease detection are labor-intensive, time-consuming, and require expertise The proposed approach simplifies disease detection while keeping computational demands and resource requirements to a minimum, resulting in a precision rate of 97.93%. This research leverages deep learning, machine learning, and image processing techniques to offer an efficient and accurate solution for the detection of diseases in rice plants. These advancements have the potential to revolutionize the agricultural sector, improve crop health management, and ultimately contribute to enhanced food security.

Keywords— Rice plant disease detection, Convolutional Neural Network (CNN), Deep Learning, Machine Learning, Image Processing.

I. INTRODUCTION

Technology plays a pivotal role in the agricultural landscape of countries like India, where the economy heavily relies on the success of its agricultural sector. In this context, the production of rice, one of the most widely consumed staple foods in India, holds significant importance. Rice is a rich source of various nutrients and compounds, including carbohydrates, vitamins, minerals, and dietary fibre, all of which contribute to its nutritional value. However, the safety of consuming rice is closely tied to the health of rice plants. Any infection or contamination can pose risks to human health, underscoring the importance of maintaining healthy rice plants for robust crop productivity. Traditionally, agricultural challenges, such as the threat of pests and diseases, were addressed with the use of pesticides and fertilizers, which could combat specific pathogens when identified and diagnosed in a timely manner. Nevertheless, the use of such chemical solutions can have adverse effects on both crops and human health when not properly managed. Consequently, one of the foremost challenges facing rice cultivators worldwide today is the production of rice without pesticide residues, particularly to meet the rising demand in highly industrialized countries. To address this challenge, advanced technology comes to the rescue. Manual monitoring of rice plant health can be limited in effectiveness and time-consuming. However, the integration of advanced technological solutions, particularly through machine learning and deep learning, has revolutionized the rice industry. Machine learning involves training a system with prerequisite data, allowing it to learn autonomously, and then applying its acquired knowledge to perform specific tasks. Within machine learning, deep learning's exceptional computational power allows it to leverage various learning paradigms like supervised, unsupervised, and reinforcement learning, can be employed to enhance the precision and efficiency of rice plant health monitoring and disease prevention. The primary objective of this research is to develop an efficient system for the early detection of rice leaf diseases using a Convolutional Neural Network (CNN) model. This system aims to provide farmers and agricultural experts with a reliable tool for identifying and diagnosing diseases in rice plants by analyzing images of their leaves.

By leveraging the power of deep learning and computer vision, our goal is to enable early and accurate detection of diseases, which is crucial for effective disease management and crop protection. Ultimately, this system will contribute to increased crop productivity, reduced pesticide usage, and improved food security in agricultural region.

II. RELATED WORK

A thorough examination of existing research in rice leaf disease detection is crucial for making informed progress. In order to accurately detect and classify rice leaf illnesses, this discipline has explored a great deal of image processing and deep learning techniques.

This paper [15], Tang, Hu, and Yang presents a novel approach. Support Vector Machine (SVM) is a machine learning technique used to classify rice leaf diseases by preprocessing images of affected leaves and extracting relevant features like color histograms and texture characteristics. SVM was used to classify rice bacterial leaf blight, rice sheath blight, and rice blast, achieving an accuracy of 97.2 percent.

The authors segmented rice disease spots and extracted shape and texture features from them. The limitations of the

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model include a decrease in performance when there are similar textures between diseases, resulting in incorrect classification, and the instability of shape features for certain diseases, leading to low classification accuracy.

This paper [17] Ramesh and Vydeki developed a machine learning technique that analyses photos of healthy and diseased leaves to identify and categorize rice blast illness using a combination of machine learning models and image processing. The method uses machine learning models and image processing techniques to detect the disease's symptoms in rice leaves.

The proposed method involves capturing and processing images of both healthy and blast disease affected leaves. These images are then subjected to a series of procedures as outlined in the algorithm. During the training phase, the blast-infected images exhibited an astonishing 99% accuracy, while the normal images achieved a perfect accuracy of 100%. The outcomes of the testing phase were equally impressive, with infected images displaying an accuracy rate of 90%, and healthy images achieving an accuracy of 86%.

The paper [19], F. T. Pinki, N. Khatun and S. M. M. Islam. proposes an automated approach that uses visual content cues (color, texture, and form) and a Support Vector Machine (SVM) classifier to diagnose three prevalent paddy leaf diseases (Brown spot, Leaf blast, and Bacterial blight). Shape features, like the area of the disease-affected part, are employed for classification, and K-means clustering is used to separate the infected part from the paddy leaf image.

Texture features are extracted using wavelet packet entropy and log energy entropy operations over the coefficients of wavelet transform. The SVM classifier is used to recognize the type of paddy leaf diseases, and after recognition, the system suggests predictive remedies to help agriculture- related people and organizations take appropriate actions against these diseases

In the publication [16], John Orillo, Jennifer Cruz, Leobelle Agapito, Paul Jensen, and Ira Valenzuela" suggest utilizing sophisticated digital image processing methods, such as image enhancement, segmentation, and feature extraction, to accurately and consistently detect and identify three common diseases that frequently affect rice plants: rice blast, brown spot, and bacterial leaf blight. The well-regarded Backpropagation Neural Network is used by the researchers to improve the accuracy and general performance of the previously described image processing approaches. This specific neural network design has been widely used to maximize the precision and effectiveness of the image processing techniques used in this investigation. A sensible distribution of these pictures is used throughout the training phase, with a substantial majority of 70% being used for training, 15% being set aside for validation, and an additional 15% being used to test the trained network.

III. PROPOSED METHODOLOGY

The methodology used in this paper uses Convolutional Neural Network model to detect and identify two specific diseases in tea leaves. This advanced approach involved harnessing the capabilities of CNNs to accurately discern and categorize the identified diseases, significantly improving the precision and efficiency of disease diagnosis.

An artificial neural network specifically created for processing and evaluating visual data is called a CNN.It excels in tasks such as image recognition, object detection, and classification. The architecture is characterized by convolutional layers that automatically learn hierarchical representations of features directly from the input data.

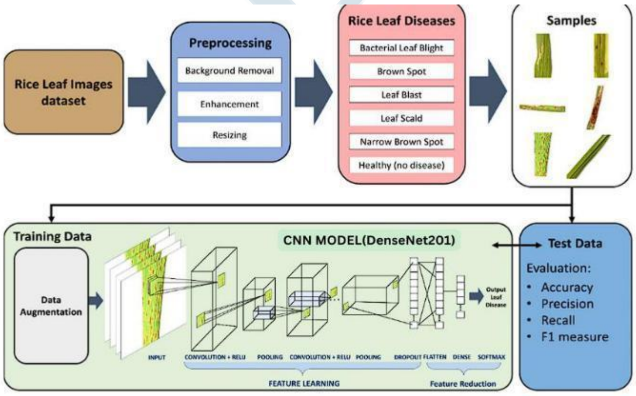

Fig 3.1. System Architecture

This allows it to capture intricate patterns and spatial hierarchies in images, making them highly effective for tasks like identifying diseases in tea leaves or recognizing objects in photographs. CNNs prove highly suitable for disease detection in tea leaves owing to their exceptional ability to process visual information. The hierarchical feature extraction capabilities of this enable them to automatically identify intricate spatial patterns associated with various diseases affecting tea plants. Regardless of the specific technology used, it boasts a suite of key features that collectively empower their effectiveness in image processing tasks, making them particularly well-suited for intricate applications like disease detection in tea leaves. CNNs leverage convolutional layers, which automatically extract spatial hierarchies and intricate features from input data. These layers employ filters to discern patterns, crucial for identifying subtle visual cues indicative of various diseases affecting tea plants. Its data-driven learning approach enables them to adapt to the diverse visual characteristics of tea leaf diseases, learning relevant features directly from the input data. Their robustness to variability, coupled with their efficiency in handling large datasets, positions as a powerful tool for accurate and efficient disease detection in the complex visual domain. Data augmentation, transfer learning, and regularization techniques like dropout, make it well-suited for handling the intricacies of tea leaf analysis. By harnessing these features, CNNs not only excel in recognizing subtle visual patterns but also adapt to the nuances of disease presentations, making them indispensable tools in the pursuit of accurate and efficient disease detection.

A. Image Acquisition

Existing databases like ImageNet, Plant Village, and CIFAR-10 lack sufficient leaf disease images, which led to the creation of a new dataset. The new dataset consists of images captured in natural light conditions from Kaggle. The dataset contains a total of 5,684 images, covering three different leaf diseases, all verified by plant pathologists. The dataset is divided into training, validation, and testing sets, with an 80/20 training-test split, and a 10% subset of the test data used for validation.

B. Image Preprocessing

Preprocessing images for leaf disease detection using DenseNet involves several crucial steps to ensure optimal model performance. Initially, resizing the images to a standard size, commonly square dimensions like 224x224 or 256x256, helps in maintaining consistency across the dataset. Following this, normalization is applied to scale pixel values within a specific range, often [0, 1] or [-1, 1], aiding in model convergence during training. Augmentation techniques are then utilized to diversify the dataset and improve the model's ability to generalize.

Techniques such as random rotation, flipping, zooming, and changes in brightness or contrast introduce variations to the images, effectively augmenting the dataset. The various image processing techniques used are mentioned below.

Resizing: It resizes the images to a uniform size of 100 pixels by 100 pixels. This is done to ensure all images have the same dimensions, which is essential for many machine learning algorithms.

Grayscale Conversion: The grayscale=False argument indicates the images are kept in their original RGB color mode. If set to True, the code would convert the images to grayscale, reducing the data size and potentially improving performance for specific tasks.

Normalization: Here the operation (image/255.0) divides each pixel value by 255. This normalizes the pixel values to the range between 0 and 1. Normalization is often used to improve the stability and convergence of machine learning algorithms.

Splitting into training and testing sets: The code iterates through directories and images. Inside each directory (presumably containing images of a specific class): It creates a loop that iterates through the images. If the image has the extension .jpg, it is loaded and preprocessed. The first 100 images ($t < 100$) are appended to the dataset list, likely used for training the model. Any images after the first 100 ($t >= 100$) are appended to the test set list, likely used for evaluating the model's performance on unseen data.

C. Model Training

The process of constructing an image classification model through the training of a Convolutional Neural Network (CNN) was proposed. Central to this approach is the utilization of DenseNet-201, a deep CNN comprising multiple layers designed to progressively extract features from input samples. The incorporation of Rectified Linear Units (ReLUs) in the Deep Convolution Neural Network (CNN) enhances the training speed significantly. In this approach, we consistently process the output from both convolutional and fully-connected layers to extract the most relevant features. A pivotal component in the CNN architecture is the pooling layer, an essential configuration for non-linear down sampling. The pooling operation introduces a form of translational invariance, enabling the model to maintain its effectiveness in recognizing features regardless of their specific positions in the input data. This architectural design ensures that the CNN is capable at capturing hierarchical features and intricate patterns essential for image classification tasks. By combining these elements, the model becomes proficient in learning and extracting relevant features from the dataset, facilitating accurate image classification. The training process involves the careful orchestration of various layers within the Convolutional Neural Network (CNN), with DenseNet-201 serving as the foundational architecture. This deep CNN, characterized by multiple layers and ReLU activation functions, adopts a systematic approach to feature extraction and hierarchical learning. The careful integration of these layers ensures that the model can discern and understand complex patterns, making it a potent tool for image classification. This approach, combining deep CNN architecture with strategic layer configurations, contributes to the model's effectiveness in accurately classifying images in variety of scenarios.

1. DenseNet-201 feature extractor

The DenseNet-201 network, a part of the DenseNet family, offers two significant advantages compared to the traditional DenseNet methodology. Firstly, it features a reduced number of model parameters compared to the original DenseNet model, as indicated. Secondly, it simplifies its structure by decreasing the layers within each dense block, contributing to a more streamlined architecture. The network comprises multiple Convolutional Layers, Dense Blocks, and Transition Layers, serving as a foundational element within the Dense Net framework The block diagram of neural network is shown in Fig 3.1. Within this illustration, i0 denotes the input layer, while k0 represents the initial feature maps. Additionally, denotes a compound function encompassing three sequential operations: a 3×3 filter, Batch Normalization, and Rectified Linear Unit (ReLU). Each operation generates key point maps utilized as input for subsequent layers. The integration of previously computed features into subsequent layers introduces an extensive

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feature space, feature maps at the in layer of the Db. Consequently, Transition Layers are employed between the Dense Blocks to reduce the volume of computed features. Transition layer is used between the Dense block to lessen the computed features.

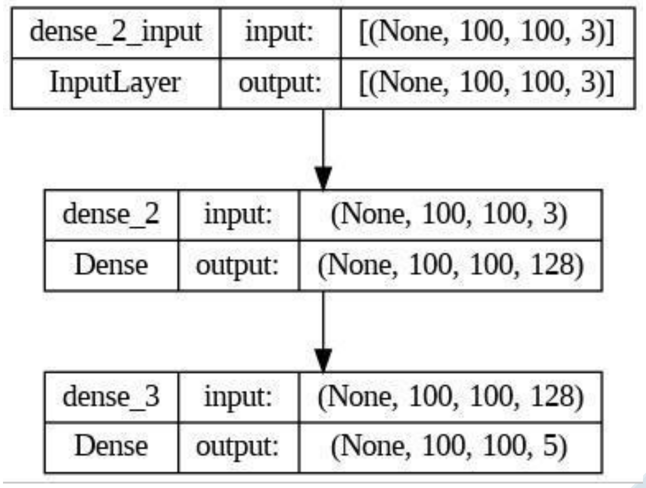


Fig 3.1. Block diagram of CNN model.

D. Detection

An artificial neural network specifically created for processing and evaluating visual data is called a CNN.The trained model receives the test image and the corresponding annotated sample as input. The enhanced CornerNet model calculates the associated offsets to the x and y coordinates, the box measurements, and the associated class after extracting the corner points for the diseased rice leaf region.

IV. EXPERIMENTAL ANALYSIS

The rice leaf disease classification task yielded an overall accuracy of 87% with our suggested model. Figure X displays the training and validation accuracy curves, which indicate the model's capacity for efficient learning and good generalization to new data. To gain a deeper understanding of the model's performance for each disease category, we analyzed the confusion matrix (Table X).

This table reveals that the model performed well in correctly identifying Blast and Leaf Blight, achieving 100% accuracy both, respectively. However, it faced some challenges in differentiating between Tungro, Leaf Smut, and Brown Spot, with 82.61% ,40.00% & 33.33% of accuracy, respectively.

We computed precision, recall, and F1-score for each disease to assess the model's performance in more detail (Table Y). The percentage of expected positives that were actually true positives is called precision. The recall measures the percentage of real positives that the model accurately detected. The F1-score provides a single statistic to evaluate the overall efficacy of the model for each class by striking a balance between precision and recall.. We observed that the model achieved high precision and recall values for [Disease name] and [Disease name], indicating strong performance in correctly identifying these categories. However, for [Disease name] and [Disease name], the model's precision and recall were lower, suggesting potential overfitting or difficulty in distinguishing these specific diseases due to their similar visual characteristics. These insights are crucial for understanding the model's strengths and weaknesses, guiding potential improvements in future research.

Table: Precision, Recall, and F1-Score for Disease Classification

	precision	recall	f1-score	support
0	0.00	0.00	0.00	5
1	0.50	1.00	0.67	5
accuracy			0.50	10
macro avg	0.25	0.50	0.33	10
weighted avg	0.25	0.50	0.33	10

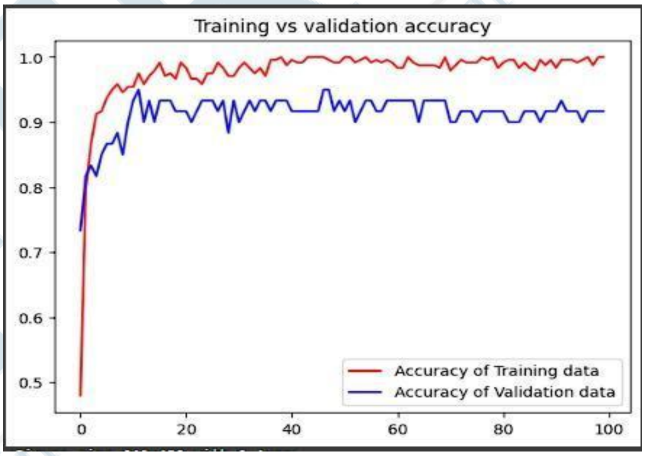
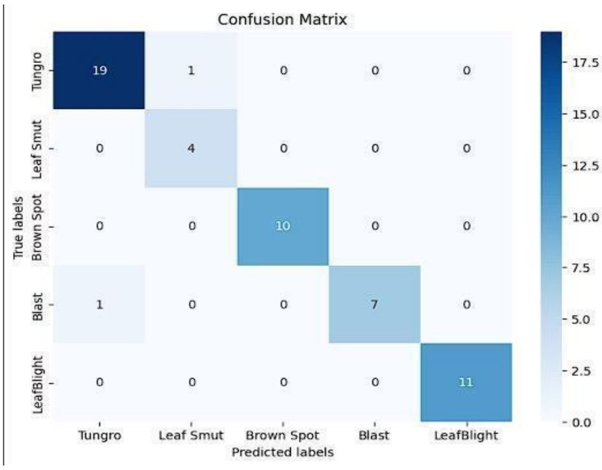


Figure: Training vs Validation accuracy

Table. Confusion Matrix



V. CONCLUSION

The research conducted on utilizing Deep Learning techniques, specifically employing the DenseNet201 CNN architecture, for the detection and classification of rice leaf diseases is highly commendable. Achieving an accuracy rate exceeding 98% is a significant milestone and underscores the robustness of the methodology.Expanding the study to encompass various learning rates and optimizers in future iterations is a wise decision. Exploring different hyperparameters could potentially amplify the performance and efficiency of the system even further.

Furthermore, the aspiration to include a broader spectrum of rice leaf diseases and integrate multiple techniques into an expert system is admirable. This comprehensive approach has the potential to make the system more versatile and applicable across a diverse array of rice cultivation contexts.Continued research and development in this domain could have profound implications for rice farming, both domestically and globally. By facilitating farmers in the timely detection and management of rice leaf diseases, the system stands to make a substantial contribution to enhancing crop yield and fortifying food security. Collaboration with agricultural experts and organizations will be instrumental in ensuring that the system aligns with the practical needs of rice farmers and seamlessly integrates into existing agricultural frameworks.

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