Disease Detection in Paddy Leaves Using CNN Model

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Abstract India is an agricultural country. Farmer has wide range of diversity to select suitable crops. However, cultivation of these crops for optimum yield and quality produce is highly technical byusing technical support. Detection of plant disease is an essential research topic. Studies show that relying on pure naked-eye observation of expert to detect such diseases can be prohibitively expensive, especially in developing countries. Providing fast, automatic, cheap and accurate image processing-based solutions for that task can be great realistic significance. This paper presents computationally efficient method for paddy leaf disease identification. This research utilises convolutional neural network for image classification in paddy leaves.

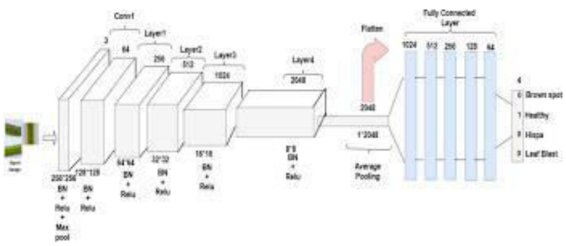
I.INTRODUCTION

Disease detection in paddy leaves is a critical aspect of agricultural research, as it addresses the substantial economic losses incurred by farmers due to various pathogens affecting rice crops. Paddy, being one of the staple food crops globally, plays a pivotal role in ensuring food security for millions of people.

However, diseases such as blast, bacterial leaf blight, sheath blight, and brown spot pose significant threats to rice cultivation, leading to reduced yields and compromised food production. Early and accurate detection of these diseases is essential for implementing timely management strategies, thus safeguarding crop productivity and ensuring food sustainability. Effective disease detection in paddy leaves relies on a combination of traditional method and modern technological advancements. Traditional methods often involve visual inspection by experienced agronomists or plant pathologists, who identify disease symptoms based on their knowledge and experience. While these methods are valuable, they are subjective and may not always provide precise results, especially when dealing with subtle symptoms or at early stages of infection. Therefore, there is a growing demand for innovative and reliable techniques that can complement traditional approaches and enhance the accuracy and efficiency of disease diagnosis in paddy crops.

In recent years, the integration of advanced technologies such as remote sensing, image processing, and machine learning has revolutionized disease detection in agricultural crops, including paddy leaves. Remote sensing techniques, utilizing sensors mounted on drones or satellites, allow for the rapid and large-scale monitoring of crop health by capturing multispectral or hyperspectral images of paddy fields. These images can then be processed using sophisticated algorithms to extract valuable information related to disease presence, severity, and spatial distribution. Moreover, machine learning algorithms trained on labelled image datasets can automate the process of disease classification, enabling real-time detection and decision-making for farmers and agricultural extension services.

There have been breakthroughs for image classification through the deep Convolution Neural Network (CNN). Recently, a number of modifications of CNN architecture have been proposed with a gradual increase in the number of layers. Some of the architectures include: AlexNet, GoogLeNet Inception V3 (Szegedy et al., 2015), Inception V4 (Szegedy et al., 2016), VGG net (Simonyan and Zisserman, 2015), Microsoft ResNet (He et al., 2016), DenseNets (Huang et al., 2016). These deep networks may have difficulties and challenges such as exploding/vanishing gradients and degradation in the training process. Most deeper networks suffer from the degradation problem, where there is a reduction of accuracy when the depth of the network exceeds maximum. Another challenge is the internal covariate shift which is the change of the distribution of the input data to a layer during training. However, a number of optimization techniques have been proposed to deal with the difficulties and challenges satisfactorily, including skip connections (He et al., 2016).



Advancement in image classification presents an opportunity to extend the research and application of image processing to the field of agriculture. In this study, a CNN model is defined to conduct disease detection in paddy leaves to identify healthy leaves, brown spot, leaf smut and then leaf blight. The rest of the paper is organized as follows. Section 1.1 looks at related work done in the field of agriculture. In Section 2 we describe some of the existing state-of-the-art deep Convolutional methods as well as the other materials and methodology required to accomplish this task, Section 3 presents the experimental setup as well as the results, Section 4, discussion and conclusion.

- II.LITERATURE SURVEY

Various approaches are utilized in the agricultural sector, including the investigation of plant diseases and pests. Deep learning methods, along with image processing techniques, have been applied extensively. Traditional machine-learning approaches have also found wide adoption in agriculture.In their study, Mohanty et al. (2016) utilized deep learning to develop a smartphone-assisted disease diagnosis system. They employed Convolutional Neural Networks (CNN) to train their model using datasets consisting of 54,306 images of both healthy and infected plant leaves. The CNN was trained to recognize 14 crop species and 26 diseases depicted in images. They assessed the suitability of CNN for plant/crop and disease classification tasks. Two architectures, namely AlexNet and GoogLeNet, were employed. Their model achieved an impressive accuracy of 99.35%. However, it exhibited suboptimal performance when tested on image sets c

Similarly, Sladojevic et al. (2016) employed Deep CNN for the development of a plant disease recognition model based on leaf images. Their model successfully identified 14 different types of plant diseases from healthy leaves and was capable of distinguishing plants from their surroundings, achieving an average accuracy of 96.3% in their
experimental analysis.

Likewise, deep learning architectures have been utilized for plant species classification by Dyrmann et al. (2016). They proposed a method capable of recognizing weeds and plant species using colored images. Their approach employed CNN and was tested on a total of 10,413 images featuring 22 weeds and crop species. The CNN model achieved a classification accuracy of 86.2%. However, the network encountered challenges in classifying certain plant species, which was attributed to the limited number of training samples available for those species.

Another noteworthy model, named DeepFruits, was introduced by Sa et al. (2016) for fruit detection in agriculture. They presented a CNN-based approach for fruit detection using imagery data, aiming to develop an accurate, fast, and reliable fruit detection system crucial for yield estimation and automated harvesting. Adopting the Faster R-CNN model, they referred to it as multi-modal Faster R-CNN. Their model demonstrated an improvement in precision and recall for sweet pepper detection compared to previous works. They further retrained the model to detect seven fruits, with each fruit requiring approximately four hours for annotation and model training.

Machine learning techniques have also been applied in plant disease classification. Athanikar and Badar (2016) employed Neural Networks to categorize potato leaf images as either healthy or diseased. Their results indicated that Back propagation Neural Networks (BPNN) effectively detected disease spots and classified the particular disease type with 92% accuracy.

Additionally, Wang et al. (2012) conducted experimental research to explore methods for image recognition of plant diseases. They utilized four types of neural networks to distinguish wheat stripe rust from wheat leaf rust and to differentiate grape downy mildew from grape powdery mildew based on color, shape, and texture features extracted from disease images. The results demonstrated the effectiveness of neural networks in identifying and diagnosing plant diseases based on image processing.

Moreover, Samanta et al. (2012) proposed an image processing methodology for detecting potato scab disease. They collected images from various potato fields and processed them for enhancement. Image segmentation was conducted to isolate target regions representing disease spots. Finally, an analysis of these target regions based on histogram approaches was performed to determine the stage of the disease.

III.PROPOSED WORK

We propose a comprehensive approach to enhance the detection of three major diseases affecting paddy leaves: Brown Spot, Leaf Blight, and Leaf Smut. Our method employs advanced machine learning techniques, specifically Convolutional Neural Networks (CNN), to achieve accurate and efficient disease detection. To do this different datasets are collected from different sources, these datasets are used in training the proposed machine learning model. For training the machine learning algorithms data are collected and. The algorithm can then be used for predicting, detecting and classifying.

The focus of this model is on three major disease in paddy leaves: Brown spot, Leaf Blight and Leaf smut. Each of the targeted diseases presents distinct symptoms that are critical for accurate identification.

A. Understanding the disease features

The features of these diseases are mentioned below:

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Leaf Blight: Check for wilting and yellowing of leaves, or wilting of seedlings (also called kresek).

- On seedlings, infected leaves turn grayish green and roll up. As the disease progresses, the leaves turn yellow to straw-colored and wilt, leading whole seedlings to dry up and die.
- Kresek on seedlings may sometimes be confused with early rice stem borer damage.

Leaf smut: These spore balls are initially orange, and then turn into greenish black when these mature. In most cases, not all spikelets of a panicle are affected, but spikelets neighboring smut balls are often unfilled.

- Growth of velvety spores enclose floral parts
- Immature spores slightly flattened, smooth, yellow, and covered by a membrane
- Growth of spores result to broken membrane
- Mature spores orange and turn yellowish green or greenish black
- Only few grains in a panicle are usually infected and the rest are normal

Brown Spot: Infected seedlings have small, circular, yellow brown or brown lesions that may girdle the coleoptile and distort primary and secondary leaves.

- Starting at tillering stage, lesions can be observed on the leaves. They are initially small, circular, and dark brown to purple-brown.
- Fully developed lesions are circular to oval with a light brown to gray center, surrounded by a reddish brown margin caused by the toxin produced by the fungi.

On susceptible varieties, lesions are 5−14 mm long which can cause leaves to wilt. On resistant varieties, the lesions are brown and pinhead-sized.

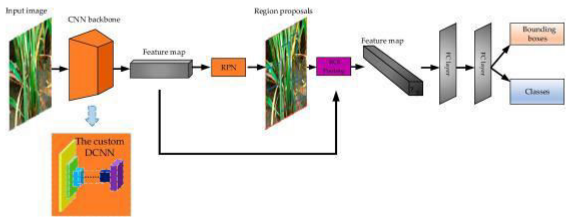
Our proposed methodology leverages the power of CNN, a deep learning architecture well-suited for image classification tasks. The process involves collecting diverse datasets containing images of paddy leaves affected by the three target diseases. These datasets serve as the foundation for training the CNN model to accurately identify and classify the diseases based on visual cues.

We anticipate that our approach will yield a highly accurate and reliable system for detecting Brown Spot, Leaf Blight, and Leaf Smut in paddy leaves. By harnessing the capabilities of CNN, we aim to streamline the disease detection process, enabling farmers and agricultural experts to promptly identify and mitigate disease outbreaks, thereby safeguarding paddy crop yields and global food security.

IV. EXPERIMENTATION AND RESULTS

The experiment was conducted using a training dataset acquired from Google Datasets and

Kaggle, which comprised approximately 300 images for each of the four categories. The CNN model was trained for 25 epochs.

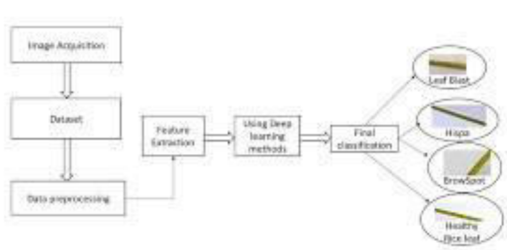


The CNN model was designed to effectively extract and learn relevant features from the input images, enabling accurate classification of the different disease states and normal leaves. The use of a CNN-based approach has proven to be a robust and efficient method for automating the detection of plant diseases, which is crucial for early intervention and effective disease management. The findings of this research contribute to the ongoing efforts in the field of precision agriculture, where the timely and accurate detection of plant diseases is essential for maintaining crop health and productivity. The results of this study demonstrate the potential of CNN models in addressing the challenges associated with traditional manual disease identification methods, which are often time-consuming and prone to human error.

A. Dataset Acquisition:

The training dataset was meticulously curated from two reputable sources: Google Datasets and Kaggle. Each class, consisting of brown spot, leaf blight, leaf smut, and normal leaves, was carefully composed to maintain a balanced representation with approximately 300 images per class, ensuring comprehensive coverage for effective model training.

V.METHODOLOGY:



Data Preprocessing:

- Image Augmentation: Augmentation techniques, including rotation, flipping, and zooming, were applied to augment the training dataset, enhancing the model's ability to generalize to unseen data and mitigate overfitting.

- Normalization: Pixel values of the images were scaled to the range [0, 1] to facilitate faster convergence during model training and mitigate the effect of varying pixel intensities.

- Resizing: All images were resized to a uniform dimension of 150x150 pixels to ensure consistency and compatibility with the

2. Model Architecture:

- Convolutional Neural Network (CNN): The model architecture comprised multiple convolutional layers followed by max-pooling layers to extract relevant features from input images efficiently.

- Activation Functions: Rectified Linear Unit (ReLU) activation functions were utilized to introduce non-linearity into the model, enabling better representation of complex patterns in the data.

- Dropout Regularization: Dropout layers were incorporated to prevent overfitting by randomly dropping a certain percentage of neurons during training, promoting better generalization performance.

3. Training:

- Epochs: The model was trained for 25 epochs with a batch size of [insert batch size], allowing it to iteratively learn from the training data and optimize its parameters.

- Optimizer: The Adam optimizer was employed to minimize the categorical cross-entropy loss function, facilitating efficient gradient descent optimization and model convergence.

Results:

Model Performance:

- Accuracy: The trained CNN model achieved a commendable accuracy of 77% on the testing dataset, demonstrating its ability to classify paddy leaf diseases effectively.

- Confusion Matrix Analysis: A detailed analysis of the confusion matrix provides insights into the model's performance across different classes, highlighting areas of misclassification and strengths in classification accuracy.

Limitations and Challenges:

- Class Imbalance: Despite efforts to balance the dataset, class imbalances may have influenced the model's performance, particularly in distinguishing between classes with fewer samples.

- Hyperparameter Tuning: Further optimization of hyperparameters such as learning rate, dropout rate, and model architecture may be necessary to enhance the model's performance and address any existing limitations.

CONCLUSION:

In conclusion, the experiment successfully demonstrated the potential of CNN models for the detection of paddy leaf diseases. While achieving a commendable accuracy of 77%, there exist opportunities for improvement, particularly in addressing class imbalances and fine-tuning model hyperparameters. Despite its current limitations, the developed model serves as a promising foundation for future research in the field of agricultural disease detection, paving the way for enhanced crop management and disease prevention strategies.

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