RICE LEAF DISEASES DETECTION USING DEEP LEARNING

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Abstract— Millions of farmers worldwide are impacted by the frequent threat that rice leaf diseases provide to rice production. Early detection and treatment of rice leaf infection are critical for rice plants to grow healthy and produce enough food for the fast growing population. Vibrant visual background complicate computer-aided diagnosis of rice leaf disease. Convolutional neural networks (CNNs) use deep learning extensively to diagnose issues by identifying the issue through a user interface by applying features that are extracted from images. The seven known common diseases of rice leaves include sheath blight, brown spot, rice yellow mottle virus, bacterial leaf blight, leaf blast, leaf scald, and narrow brown spot. This research aims to improve automatic plant disease detection and analysis, providing solutions for early disease detection, disease prediction, and pesticide recommendations. By using CNN technology, it is possible to solve complex agricultural problems with an accurate and effective user interface and guarantee that rice production remains sustainable in the face of rising global food demands.

Keywords—Convolutional Neural Network (CNN),Deep Learning, Artificial Intelligence, and Rice leaf.

Introduction:

One major food crop grown worldwide is rice. Nearly 3 billion people depend on rice for their daily sustenance, therefore a high and steady output is essential to global food security. However, the world's rice supply has dropped recently due to problems with global climate change, water scarcity, diminishing soil and a decline in farmers' demand for rice. Most of the nutrients needed for crops to develop sustainably are found in the soil, including potassium, phosphorus, nitrogen, and all trace elements.

Javidam et al., propose an advanced algorithm for grape leaf disease diagnosis in smart agriculture. Automatic background removal, Otsu and K-means picture segmentation, GLCM, LBP, and HOG feature extraction, and PCA for dimension reduction are all part of their methodology. The method beats CNN and GoogLeNet in grape leaf disease classification, demonstrating improved accuracy and faster processing times while addressing issues like shadow interference[1].

Reyana et al., leverage multisensor data fusion and machine learning, showcasing the superiority of the random forest algorithm for crop yield forecasting. The study highlights the importance of several metrics in agricultural production forecasts and promotes multisensor machine-learning technologies to address global food security challenges. It also provides advice for better crop farming[2].

Farmonov et al., use DESIS hyperspectral imagery and SVM, RF, and wavelet attention CNN in southeastern Hungary for accurate crop type mapping. Crop monitoring, yield prediction, and global food security are all impacted by this work, which emphasizes the use of hyperspectral imaging and machine learning in effective agricultural management and decision-making.[3].

Mokhtar et al., focus on multi-step time series forecasting of drought for sustainable water resource management. Their research focuses on drought occurrences and their effects on plants, integrating data analysis, machine learning algorithms, and original manuscript writing. The paper discusses spatiotemporal dynamics over the Tibetan plateau and drought episodes in China, including works on drought prediction utilizing climatic data and a stacked LSTM model[4].

Kashyap et al., provide a comprehensive review of soil moisture and nutrient monitoring techniques, spanning from laboratory-based methods to remote sensing and emphasizing recent advances for cost- effective, portable systems. The paper advocates for technology adoption in precision agriculture, contributing to sustainable crop production through enhanced monitoring methodologies[5].

GAO Peng et al., examine a 38-year study on organic, inorganic, and combined fertilization's impact on soil fertility and rice yield, demonstrating sustained organic and combined approaches enhance soil organic carbon, positively influencing rice productivity. The study highlights the possibility for inefficient soil fertility augmentation, with the maximum agricultural production using the NPKM combination strategy[6].

Zhang et al., introduce a dual generative adversarial network (GAN) high-quality picture augmentation method. In order to increase image quality, the technique employs a GAN network for image super-resolution in addition to one for image production. The paper addresses the issue of the lack of high- quality training data in agriculture by providing a workable and reasonably priced method of improving the disease recognition skills of deep learning models[7].

Patil et al., propose a novel method, Rice- Fusion, combining Convolutional Neural Network with agricultural IoT for accurate rice leaf infection diagnosis. Extensive experimental validation reveals exceptional accuracy, highlighting the potential to transform illness diagnosis and encourage the establishment of healthy rice plants.[8].

Shovon et al., presented PlantDet, a strong multi-model ensemble with sophisticated features addresses the issues of underfitting and overfitting for precise rice and betel leaf disease diagnosis. The tool, outperforming state-of-the-art models, aids early diagnosis, empowering farmers for improved crop management and agricultural productivity[9].

Wang et al., present SAFFPest, a model combining VarifocalNet, self-attention, and group normalization, addressing limitations in detecting variable-shaped rice pests. The model exhibits superior accuracy in identifying nine pest types, particularly excelling in detailing features of irregularly shaped pests, with promising implications for precise pest identification and agricultural sustainability[10].

Ahmed et al., study machine learning algorithms, such as decision trees and logistic regression, and they find that these algorithms can detect and categorize rice plant diseases with accuracies ranging from 50% to 98%.The study underscores the potential of these tools for rapid and accurate disease identification, enhancing crop management and overall agricultural productivity[11].

Vasantha et al., emphasize machine learning's crucial role in early detection of rice plant diseases for enhanced crop yield and quality. The paper highlights deep learning, especially convolutional neural networks (CNN), as effective in achieving high accuracy for automated rice leaf disease classification, providing promising solutions for farmers to maintain crop health and productivity[12].

Rashid et al., gives a comprehensive overview of machine learning applications for agricultural yield prediction with a particular emphasis on palm oil production. Analyzing 223 articles, the paper evaluates datasets, features, algorithms, and system performance. It focuses on the palm oil sector and critically evaluates cutting-edge methods, pointing out advantages and disadvantages in an effort to stimulate more study on the relationship between crop output and palm oil production prediction in agriculture[13].

Diseases that affect farmers also represent a serious threat to rice output in paddy fields. Timely diagnosis is essential to minimize possible harm. In addition to protecting rice plants from harm, disease detection and treatment promote robust growth, which raises crop yields overall. A new method uses a smartphone to take pictures and has an intuitive user interface to quickly classify diseases and suggest treatments.

Data collection:

The compilation of their dataset for the purpose of detecting rice leaf disease stands as a prime example of a methodical and comprehensive methodology. Table 1 depicts, encompassing images of bacterial leaf blight (449), blast (707), brown spot (40), healthy leaves (675), leaf smut (693), rice yellow mottle virus (22), sheath blight (516), and tungro (556), serves as a testament to its diversity. The goal was to capture the entire spectrum of rice leaf states, aiming to facilitate the creation of machine learning models that showcase the ability to accurately identify and differentiate between various illnesses.

S.No	Name of the Diseases	Number of Images
1.	Bacterial leaf blight	449
2.	Blast	707
3.	Brown spot	40
4.	Healthy	675
5.	Leaf smut	693
6.	Rice yellow mottle virus	22
7.	Sheath blight	516
8.	Tungro	596
	Total	**3698**

Table 1: Number of images displaying diseases affecting rice leaves.

Fig 1. Images Of Rice Leaf Diseases

The first dataset that is being examined is the Rice Leaf dataset, which is accessible to the general public on Kaggle. This dataset includes seven different diseases and one category that represents healthy rice plants.

Data preprocessing:

Modern methods for preventing plant diseases are vitally needed, given the rising challenges the agriculture sector is experiencing. This study addresses the critical issue of identifying rice leaf disease using deep learning techniques. Using convolutional neural networks (CNNs),developing a scalable and reliable model with the goal of classifying rice leaf diseases automatically. The study's dataset was meticulously chosen, and it contains a broad variety of images depicting both healthy and damaged rice leaves. This pipeline adds variability to the training set and improves the model's capacity to generalise by standardising pixel values, rotating, moving, and flipping images, as well as resizing them to a standard format. A variety of image enhancing approaches are investigated to highlight disease-related elements in the images, including contrast stretching, histogram equalisation, and spatial filtering. This study investigates transfer learning utilising pre- trained CNN models by integrating PCA for computing efficiency and preventing overfitting, all while utilising large-scale datasets. The ultimate goal is to develop a real- time, precise system for identifying rice leaf diseases, optimizing crop management, empowering agriculture, and alleviating the financial impact of plant diseases on global food security through timely and accurate information for farmers.

Data augmentation:

Technique	Range
Rescale	1/255
Rotation	40
Width Shift	0.2
Height Shift	0.2
Shear	0.2
Zoom	0.2
Horizontal Flip	True
Fill Mode	Nearest

Table 2: Augmentation techniques with their range.

The augmentation of dataset diversity is achieved through employing robust data augmentation techniques, introducing variations to existing photos via transformations such as rotation, scaling, cropping, and flipping. Pixel values are then normalised to a standardised scale, typically ranging from 0 to 1 or -1 to 1, ensuring uniformity in model learning. Furthermore, resizing images is essential to balance their sizes for optimal CNN processing. A meticulous division of the dataset into test, validation, and training sets is implemented, with the training set enabling model training, the validation set minimising overfitting, and the test set serving as a critical evaluator of model performance. To enhance training dataset quality and diversity, an ImageData Generator with key augmentation parameters is utilized for image-based machine learning. Transformations during training, including rotation (up to 40 degrees), shifting (20% width and height), shear, zooming (20%), and horizontal flipping, improve the model's adaptability. The "nearest" fill mode maintains data relevance and coherence, ultimately boosting the model's ability to identify and classify diseases by expanding and preparing the training data for real-world conditions.

Methodology:

This work suggests a deep learning mechanism for identifying rice leaf diseases. Images of rice leaves in various prevalent diseases as well as healthy conditions were gathered to create a diversified dataset that was ready for training.The subsequent stages entail the comprehensive development and analysis of a deep learning model designed for the detection of rice leaf disease.This study's deep learning methodology for rice leaf disease detection makes use of neural networks to improve accuracy and efficiency.

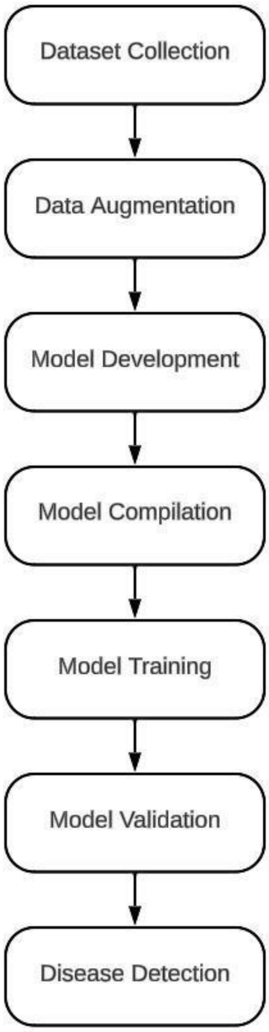

Fig 2. Flowchart Outlining The Proposed Methodology To Illness Identification.

The first step is to gather a large dataset of images of rice leaves that are both healthy and diseased. This dataset must be used for both training and validating the deep learning model. To ensure the model's durability and improve its generalization abilities, preprocessing techniques including image augmentation and normalisation are applied. Convolutional Neural Networks, or

CNNs, are frequently used for image-related tasks; in this context, they are specifically designed to learn and extract features that are unique to certain diseases. The model is fed labelled photos throughout the training phase, and its parameters are adjusted to maximise performance.A separate set of images that were not utilised for training is used for validation in order to assess the model's effectiveness.Another option is transfer learning, which applies previously learned models to sizable datasets and modifies them to account for the unique characteristics of rice leaf diseases.Performance indicators such as precision, recall, and F1 score are computed to assess the model's ability to discriminate between healthy and unhealthy rice leaves.The detailed methodology, which takes a rigorous approach to everything from model selection and dataset preparation to training, validation, and testing, ensures an effective and accurate deep learning solution for rice leaf disease detection.

Result and Discussion:

The convolutional neural network (CNN) for rice leaf disease classification that is the result of the deep learning model training is shown and explained in the following.The training procedure comprises 100 epochs, wherein every epoch encompasses a comprehensive traversal of the whole dataset, comprising 118 mini-batches.The "loss" measure, which begins at 1.9348 in the first epoch, represents the performance of the model and is meant to be minimised over time. Simultaneously, the "accuracy" metric, which starts at 0.2562, represents the model's competence with the training set and becomes better throughout the course of the epochs.The iterative display of output for every epoch illustrates how the learning process of the model is dynamic.Reaching a situation where accuracy is maximised and loss is minimized.The proposed convolutional neural network (CNN) architecture demonstrated excellent performance on the huge testing dataset, with an overall accuracy of 87%.Even if the results are encouraging, it's important to recognise that plant diseases are dynamic and that continuous model improvement is required. Collaborative efforts with domain experts, such as plant pathologists, are vital for enhancing model interpretability and addressing complex agricultural challenges. The study's training dynamics provide insights into the deep learning model's effectiveness, enabling a thorough assessment of its capability for rice leaf disease detection.

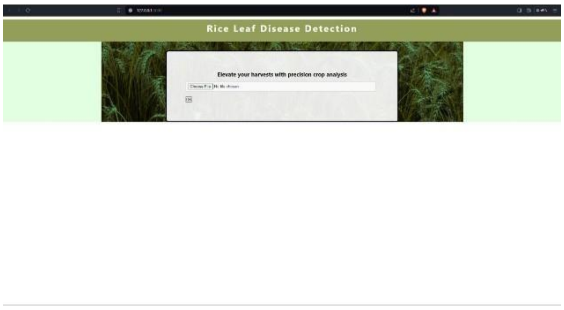

Fig 3. Webpage For Uploading Rice Leaf Images For Disease Detection

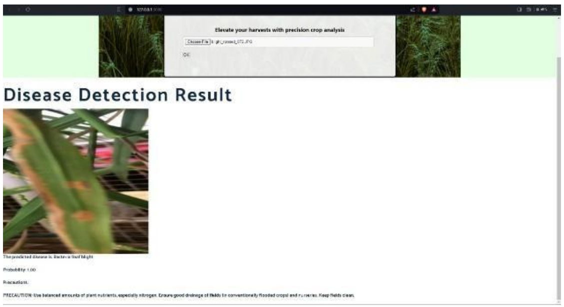

Fig 4. Web interface for rapid rice leaf disease detection with recommended precautions.

Fig 3 illustrates a user-friendly web platform, enabling quick processing and real-time display of results in an understandable format. The system not only identifies diseases but also offers insightful recommendations and safety measures tailored to the specific illness, facilitating rapid assessment of crop health.Fig 4 depicts controlling the amount of nutrients in rice fields is essential for reducing the impact of the sheath blight disease.It is crucial to maintain an ideal ratio of important nutrients, including potassium, phosphorus, and nitrogen.

Conclusion:

The plant disease diagnosis systems in agriculture, particularly for rice leaves, have significant limitations, relying on subjective and error-prone human inspections, often detecting diseases only at advanced stages. Manual data collection causes delays, and these systems lack predictive capabilities, depend on experts, and lack user-friendly interfaces.Our current work focuses on a methodical approach to solving difficulties in the identification of plant diseases. This project uses a lot of data-driven processes to develop a comprehensive model for precise disease identification, including feature extraction, preprocessing, data gathering, and deep learning techniques. By highlighting the significance of data augmentation and normalization for enhanced model performance, the findings promote precision agriculture.

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