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Predicting Rice Crop Diseases Using CNN Based Image Classification

[1]Boddu Likith Satya Surya Swaroop,[2]Ganta Geethika Sri,[3]Ramayanam Mohana Anusha,
[4]Gandarapu Akhil Soma Sekhar, [5]Mr.K S R Prasad
[1,2,3,4]U. G Student, Department of Artificial Intelligence & Data Science,
D.N.R. COLLEGE OF ENGINEERING & TECHNOLOGY (AUTONOMOUS)
Balusumudi, Bhimavaram, West Godavari District, Andhra Pradesh -534202
[5]Assistant Professor, Department of Artificial Intelligence & Data Science,
D.N.R. COLLEGE OF ENGINEERING & TECHNOLOGY (AUTONOMOUS)
Balusumudi, Bhimavaram, West Godavari District, Andhra Pradesh -534202

ABSTRACT

Agriculture is the backbone of global food security, and rice, being a staple crop, plays a vital role in feeding a large portion of the world's population. However, rice production is severely threatened by various rice crop diseases that reduce yield and quality. Traditional detection methods rely on manual observation and expert knowledge, which are often time-consuming and inefficient. To overcome these limitations, this study proposes a CNN-based image classification system for automatic rice leaf disease detection. The model processes rice leaf images to classify them as healthy or diseased with high accuracy. A diverse dataset of rice leaves affected by bacterial blight, blast, and brown spot is used for training and evaluation. Deep learning techniques enable effective feature extraction and precise disease classification without manual intervention. The system supports early identification of diseases, thereby minimizing crop losses and enhancing productivity. Experimental results validate the robustness of the CNN model in real-time detection. This approach provides a scalable and efficient solution for smart agriculture, empowering farmers with reliable decision-making tools.

KEYWORDS ***Deep Learning, ResNet9 CNN, Flask web application, Image preprocessing, Computer Vision***

INTRODUCTION

Agriculture is essential to maintaining rural economies, guaranteeing global food security, and providing a living for

millions of people. Crop production, however, is extremely susceptible to a number of illnesses that can significantly lower output and quality. Since these plant diseases frequently spread quickly, early detection is essential to avoiding significant losses in agriculture. Conventional disease detection techniques depend on farmers' or agricultural specialists' visual inspection, which is useful but frequently laborious, arbitrary, and unfeasible for extensive surveillance. Developments in computer vision and artificial intelligence (AI) have enabled the creation of automated disease detection systems that are more accurate, quicker, and available to a larger population. Images of plant leaves can be uploaded to the system, where they are pre- processed, examined, and categorized into one of 38 supported categories that include both healthy and diseased states across a variety of crops, including tomato, corn, apple, grape, and potato.This system seeks to enable farmers, researchers, and agricultural extension professionals to act promptly by offering real-time forecasts in addition to comprehensive disease information and treatment suggestions. The application may be utilized in a variety of settings, from distant farms to laboratories, thanks to its adaptable, mobile-friendly design, which eliminates the need for extensive technical knowledge.

RELATED WORK

The Crop Disease Identifier is an AI-based tool that helps farmers detect plant leaf diseases quickly using image recognition. It works by training a deep learning model (CNN) to identify disease patterns in different crop leaves.the model learns from thousands of labeled leaf images to distinguish between healthy and infected ones. Techniques like image resizing, normalization, and data augmentation are used so the model can perform well on real-world photos. The system is deployed through a Flask web app, where users can upload a leaf image and instantly receive the disease name along with treatment advice. It’s lightweight, fast, and can even run on mobile devices. This makes it a practical and affordable solution for farmers to detect problems early, cut down on pesticide waste, and protect crop yields for sustainable agriculture.

LITERATURE REVIEW

The literature review establishes a foundation for the purpose understanding advancements in plant disease detection

using deep learning while identifying existing research gaps. Mohanty et al. (2016) demonstrated the potential of CNNs with high accuracy in lab settings, while Ferentinos (2018) confirmed their superiority over traditional models but stressed the need for diverse datasets. Sladojevic et al. (2016) introduced one of the first mobile-based detection systems, proving feasibility but with limited crop coverage. Atila et al. (2021) enhanced model robustness by combining CNNs with Transformers, and Ramcharan et al. (2017) showed that Transfer Learning enables strong results even with smaller datasets. Collectively, these studies reveal both progress and persistent challenge particularly in dataset diversity and real-world generalization thereby guiding this study's aim to develop a more adaptable and accurate plant disease detection system.

EXISTING METHOD

Plant disease detection methods fall into three main categories. The first is manual visual inspection, where experts identify diseases by closely examining plants; this approach is slow, subjective, and requires skilled knowledge. The second category involves traditional machine learning, which uses handcrafted features such as color, texture, and shape, along with classifiers like SVM or Random Forest. Although useful, these methods often face challenges in accuracy and adapting to different crops or environments. The third and most advanced approach employs deep learning models, which automatically learn important features from images, leading to higher accuracy. However, these models may struggle to generalize well to new or varied real-world data unless trained with diverse datasets and fine-tuned carefully. Data augmentation and preprocessing techniques are essential to improve their robustness. The following section will explain the proposed method, dataset preparation, and implementation strategies used to build a scalable and effective crop disease detection system.

PROPOSED MEHOD

The system uses a deep learning approach based on ResNet9 CNN, moving beyond traditional machine learning models with handcrafted features to achieve higher accuracy and adaptability. Through transfer learning and advanced preprocessing, the model generalizes effectively under diverse real-world conditions such as varying lighting, angles, and backgrounds. In addition to disease detection, it provides integrated recommendations that offer farmers reliable treatment suggestions. The system supports both offline and cloud

deployment, enabling use in remote areas without internet access while also allowing cloud-based scalability for wider reach. Designed with a farmer-friendly interface, the responsive web application ensures ease of use for both experts and non-experts, bridging the gap between advanced technology and practical agricultural needs.

SYSETM ARCHITECTURE

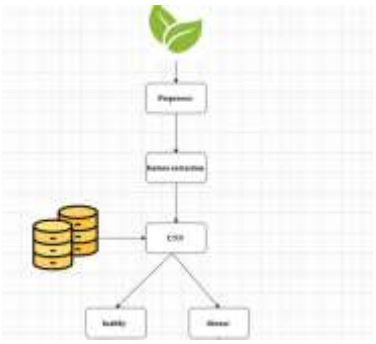

Figure 1: Block Diagram

METHODOLOGY DESCRIPTION

The Crop Disease Identifier system undergoes thorough testing to ensure reliable performance under various conditions. The model must handle changes in lighting, orientation, image quality, and background noise while working across different crop species. Interpretability testing ensures that the predicted disease matches expert expectations and provides clear information about symptoms and treatment. Misclassifications are reviewed for potential biases. Reproducibility is ensured by fixing model weights and controlling random variables, so the system produces consistent results with the same input.

Data preprocessing is tested to ensure proper resizing, normalization, and conversion, with non-image files being rejected. Performance testing ensures quick results (2–3 seconds on a CPU and faster on a GPU) and the ability to handle multiple concurrent requests. Security testing ensures only allowed image formats are uploaded and prevents malicious file uploads. The web interface is tested for a smooth, user-friendly experience with a layout optimized for various screen sizes and resolutions, ensuring usability on all devices.

Finally, usability testing confirms that the system is accessible, intuitive, and easy to farmers and students, providing accurate disease identification and the process treatment recommendations. These tests guarantee the system's robustness, security, and usability.

RESULTS AND DISCUSSION



Figure 2.1: login and register page

In this project started with login or sign up page. if we give details it will open home page. then we can see there with train and detect process of the project.

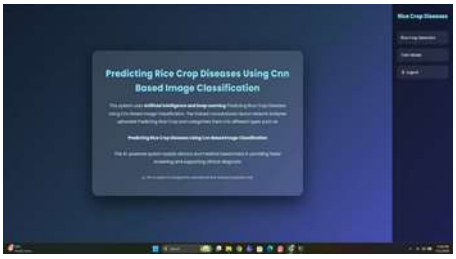

Figure 2.2: Home Page

Here we can see all option to page of right of home page.



Figure 2.3: Random Dataset Samples

If we clicked training it can complete and it will show accuracy, samples of images and more graphs above.



Figure 2.4: Upload Image

After training if we clicked detection page there need to browse input image like above.

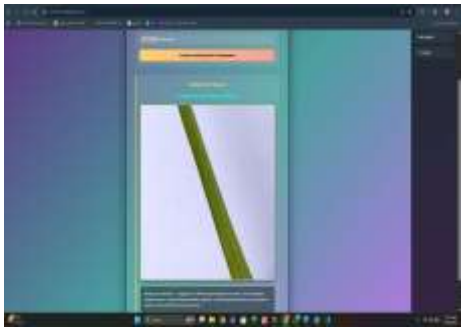

Figure 2.5: Analyze Rice Crop Disease Normal

After uploading picture based on features it showing as Normal in above figure.



Figure 2.5: Analyze Rice Crop Disease Bacterial Leaf Blight

Finally, after uploading picture based on features it showing as Normal in above figure.

CONCLUSION

The Crop Disease Identifier is an efficient, AI-driven diagnostic tool that uses a ResNet9 model to accurately classify 38 distinct crop diseases from leaf images.

The web-based platform proved reliable, consistently delivering high-precision results that significantly reduce the errors and delays of manual inspection.

FUTURE WORK

Future work will focus on system

scalability and transitioning to a proactive disease advisory system, moving beyond simple detection to preventive management.Key enhancements will integrate IoT-enabled sensors for real- time monitoring and develop a mobile application with an offline mode for remote accessibility. Furthermore, the system will incorporate Weather and Soil data via API to predict potential disease outbreaks. Finally, the detection model's core will be upgraded using a more advanced architecture like a Vision Transformer (ViT) to provide a complete and advanced solution for smart agriculture.

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