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SIGNIFICANCE OF DATA AUGMENTATION IN IDENTIFYING PLANTS DISEASES USING DEEP LEARNING

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Abstract:

In recent years, rice infections have received an increasing amount of attention. Damage to rice plants leads to lower rice production. Identification of rice diseases early is essential for crops. However, conventional disease detection techniques are not very effective in doing so. Recent advances in convolutional neural networks have resulted in noticeably better images. Because of its excellent classification accuracy, it is particularly well suited for identifying various plant diseases. Plant diseases must be recognized when monitoring crops using technology-based methods. Recent research has demonstrated that CNN (Convolutional Neural Network) is the most efficient deep learning technique for processing leaf image data for illness diagnosis. Processing full leaves also increases computational cost and time, lowering training quality and performance. In order to increase the training sample size and boost classification accuracy, data augmentation is crucial. The classification of the enriched rice-leaf picture data set is thus carried out in our work using the Resnet model. This method is effective, as shown by the trained model's accuracy of 98.10% on the test dataset. This research work has attempted to enhance the performance of the model with and without data augmentation.

Keywords: Low Light Image Enhancement, Deep Learning, Image Enhancement, Low Light Vision, Dark Image Processing, Low light image restoration, neural networks for low light, enhancing visibility in low light image, denoising, image dehazing, noise reduction.

1. INTRODUCTION

In India and globally, rice serves as a staple food, making its production and quality critical for food security. However, rice cultivation faces numerous challenges, particularly from diseases that can affect the plant at various stages of growth. Timely identification and treatment of these diseases are essential to ensure both high yield and quality of rice production. The increasing prevalence of plant diseases, coupled with the limitations of manual detection methods, highlights the need for automated solutions. Traditional methods, such as visual inspection by detected early, causing significant losses in crop yield and quality. Recent advancements in machine learning, particularly in deep learning, have demonstrated remarkable potential in addressing these challenges. Convolutional Neural Networks (CNNs) have emerged as the most effective technique for analysing leaf images and diagnosing diseases. These models can process vast amounts of image data, extracting complex features that enable precise disease classification. However, the effectiveness of CNNs is limited by the availability of large and diverse datasets. Small or imbalanced datasets often lead to over fitting, reducing the model's generalization capabilities. Additionally, processing full leaf images increases computational cost and training time, further complicating the implementation of such systems. Overcome these challenges, this study explores the role of data augmentation in improving the performance of CNN-based models for plant disease detection. By artificially enlarging the dataset with transformed versions of existing images, data augmentation enhances the training process, reduces over fitting, and improves model accuracy. The ResNet architecture, known for its superior feature extraction capabilities and efficient gradient flow, is employed to classify rice leaf diseases with and without data augmentation. This research highlights the significance of early and accurate disease detection in agriculture, paving the way for scalable and automated solutions to enhance crop health monitoring and productivity.

Fig. 1. Different Diseases in Rice

In many real-world scenarios, images captured in low-light conditions suffer from poor visibility, noise, and loss of detail. These images are often characterized by low contrast, dark regions, and reduced overall quality. Therefore, it is essential to build a system or model to improve the quality of images captured in low-light and non-uniform lighting conditions.

2.LITERATURE SURVEY

This study presents an innovative approach for plant leaf disease analysis using image processing techniques combined with a modified Support Vector Machine-Classification and Regression (SVM-CS) classifier. By processing high-quality images of plant leaves, the method aims to accurately classify and diagnose diseases, improving agricultural productivity and sustainability. The study demonstrates significant advancements in precision and

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computational efficiency over traditional methods, making it a valuable tool for modern agriculture.

This work introduces a fully automated method for detecting and quantifying symptoms of leaf diseases using digital image processing. The proposed technique provides precise measurements of affected areas, enabling rapid disease diagnosis and monitoring. The approach leverages advanced image processing algorithms to handle various plant species and disease symptoms, offering significant potential for integration into agricultural management systems.

This study investigates how dataset size and diversity influence the performance of deep learning and transfer learning models in plant disease classification. Through extensive experiments, the research highlights the critical role of large, varied datasets in enhancing model accuracy and generalizability, paving the way for more robust applications of AI in agriculture.

This paper explores an enhanced approach for plant leaf disease classification using a snapshot ensemble Convolutional Neural Network (CNN). The method employs advanced ensemble learning techniques to improve the robustness and accuracy of disease detection across diverse datasets. Experimental results underscore the efficacy of the proposed approach in achieving superior classification performance

This study utilizes Convolutional Neural Networks (CNNs) for detecting plant diseases with high precision. The research emphasizes the importance of image preprocessing and data augmentation techniques to address challenges like over fitting and small datasets. Results demonstrate the proposed model's potential to aid in efficient and accurate disease detection for various crops.data leakage challenges worldwide.

This research focuses on identifying diseases in peach leaves, particularly bacteriosis, using deep learning techniques. The study employs CNN architectures to analyze visual symptoms and evaluate disease severity, offering significant improvements in early detection and accurate classification. The findings highlight the potential of AI-driven tools in modern plant pathology.

This paper compares the effectiveness of transfer learning models in detecting diseases in bell pepper plants. By leveraging pre-trained architectures, the study addresses challenges such as small dataset sizes and complex disease patterns. The results demonstrate the superior performance of transfer learning in achieving high classification accuracy.

This study presents a novel deep learning-based framework for autonomously estimating the severity of plant diseases from images. The system processes high-resolution visual data to identify disease patterns and quantify damage, offering a scalable and efficient solution for agricultural monitoring and management. This research develops a multiclass deep convolutional neural network classifier to detect anomalies in rice plants. By training on a diverse dataset, the model achieves high accuracy in identifying multiple disease types, providing a critical tool for precision agriculture and crop health monitoring.

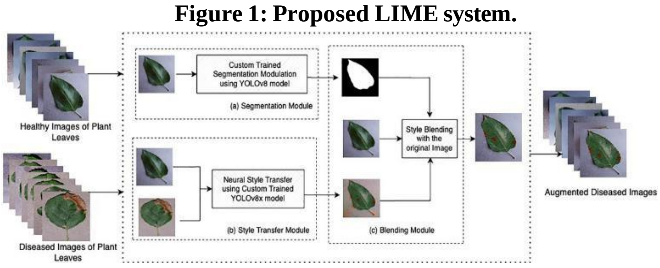
This study evaluates the performance of deep CNN-based models for detecting and localizing cracks in concrete structures. The research emphasizes the robustness of these techniques in handling real-world scenarios and varying environmental conditions, providing a reliable method for infrastructure maintenance and safety assessment.

3.PROPOSED METHODOLOGY

The proposed system aims to enhance plant disease detection by integrating advanced deep learning techniques with effective data augmentation. This system uses the ResNet-50 architecture to classify enriched rice leaf datasets, aiming to improve model accuracy and robustness. Data augmentation techniques such as scaling, translation, and rotation are employed to expand the dataset, addressing issues of overfitting and improving generalization. Before parallel processing begins, it's essential to preprocess and prepare your datasets. This includes cleaning the data, handling missing values, transforming the data (e.g., normalizing, encoding), and splitting large datasets into manageable chunks for parallel execution. components: Rotating images to create new perspectives. Horizontal and vertical flipping of images. Modifying brightness, contrast, or saturation to simulate different lighting conditions. Introducing slight variations or noise to images to simulate environmental conditions. A large, diverse dataset with variations created from the original set. The augmented dataset helps expose the model to a broader range of conditions and scenarios. A convolutional neural network (CNN) is trained on both the original and augmented datasets. The model learns features from both the original and augmented images, improving its generalization ability.

The trained model can now identify plant diseases more accurately, even under varied real-world conditions (e.g., different lighting, angles, backgrounds). The model is less prone to overfitting and performs better on unseen images.Evaluation and Benchmarking: LIME's performance is often evaluated against benchmark datasets of low-light images. It aims to outperform or match existing state-of-the-art lowlight enhancement methods in terms of image quality metrics.

Figure 1: Proposed LIME system.



The proposed methodology typically includes the following key LIME's enhanced images can be used in a wide range of applications, including: Surveillance systems (improving nighttime video quality) Astrophotography (capturing stars and galaxies in low-light conditions),Consumer photography (improving smartphone camera performance in dimly lit environments).

Advantages:

LIME is a technique that leverages deep learning and image processing to enhance images captured in low-light conditions. It offers several advantages, making it a valuable solution for various applications: Improved Accuracy: The system achieves an accuracy of 98.10% on test datasets due to the integration of ResNet-50 and data augmentation. Automatic Enhancement: While customization is available, LIME can also operate with default settings, making it suitable for users who may not have expertise in image processing.

Realism: LIME's enhancements are designed to maintain the natural and realistic appearance of the scene. It avoids overprocessing that can result in unnatural-looking images.

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Quality Metrics: The algorithm often includes the calculation of image quality metrics like PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index), allowing users to objectively measure the improvement in image quality.

Versatility: LIME is versatile and applicable in various domains, including surveillance, consumer photography, astronomy, medical imaging, and more. It addresses the common challenge of low-light conditions in these fields.

4.EXPERIMENTAL ANALYSIS

To increase yield quality, quantity, and productivity, it is essential to detect pests and illnesses early and use less pesticides to minimize harm to crops and the environment. This study's primary goal was to identify and categories four types of rice leaf diseases images of rice leaves were utilised in this study to identify disease using a Resnet-based model. It was also contrasted against CNN and a few other deep

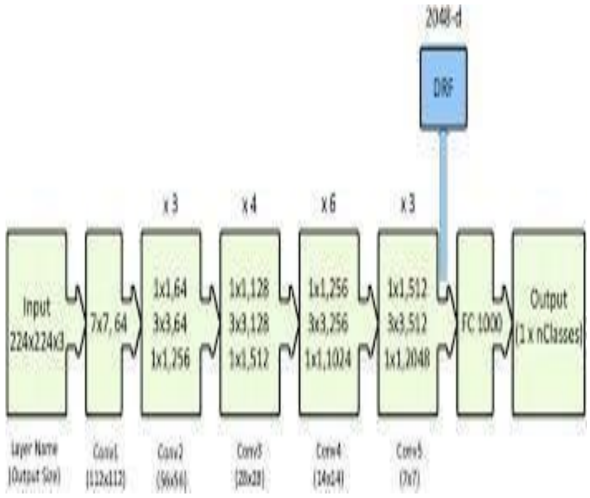

Fig. 3. Resnet Architecture

Fig. 4. Augmented Images

TABLE II
TRAINING AND VALIDATION LOSS ACCURACY (WITH AUGMENTATION)

Based Model	Training Loss	Validation Loss
VGG 16	1.098	0.896
VGG 16 (with first three block of frozen)	1.012	0.824
VGG 19	0.855	0.760
Xception	1.745	0.710
Resnet50	0.840	0.625

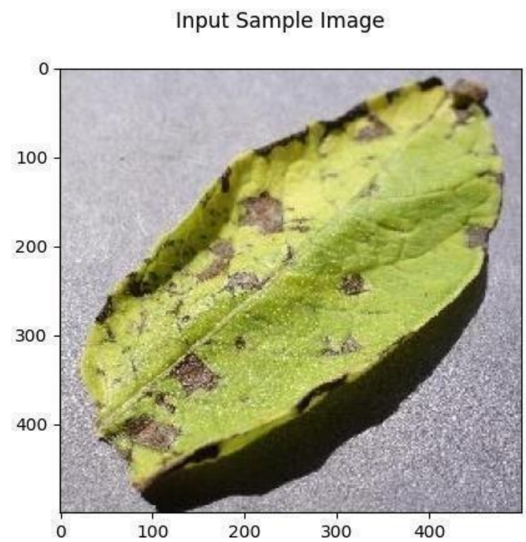

Fig. 5. Sample Image

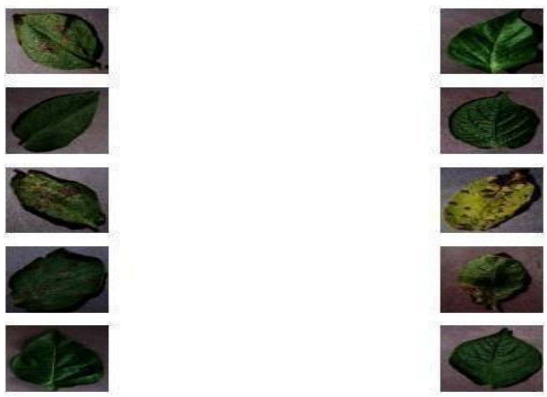

Fig. 6. Test Transformation Leaf's precision

TABLE III
PRECISION OF DEEP LEARNING ALGORITHMS

Based Model	Training Loss	Validation Loss
VGG 16	1.098	0.896

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VGG 16 (with first three block of frozen)	1.012	0.824
VGG 19	0.855	0.760
Xception	1.745	0.710
Resnet50	0.840	0.625

Fig. 7. Hue and Saturation

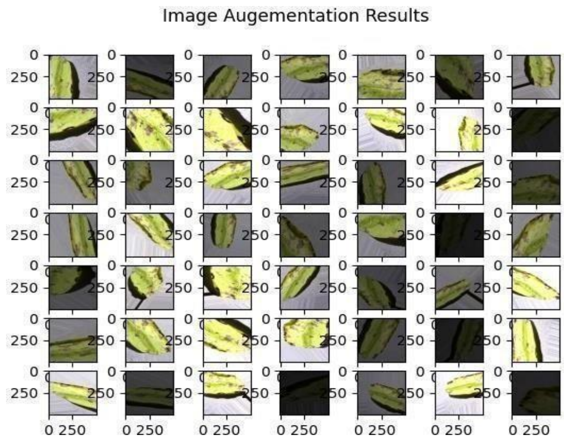

Fig. 8. Simulation results of data augmentation result

neural network architectures. Sets of data on rice leaves from plant villages are used for this were categorized in this study utilizing a variety of DL techniques. We processed different datasets of infected rice leaves using multiple well-known deep learning techniques, including VGG19, VGG16, Xception, andResnet50. The results demonstrate that Resnet50 model has the highest accuracy (98.10The development of effective detection techniques employing big datasets with various plant leaf diseases, however, will have a significant impact in the future. This also tackles the issue of class imbalance by necessitating substantial generic datasets. It will be simpler for farmers to secure their crops when more diseases are found. To improve disease detection simpler and quicker in the future, it will concentrate on including new diseases and algorithms.

5.CONCLUSION

The study underscores the critical role of data augmentation in improving the efficiency and accuracy of deep learning models for plant disease detection. Traditional approaches faced limitations such as small dataset size, overfitting, and poor generalization, which were effectively addressed by integrating data augmentation techniques like scaling, rotation, and translation. By leveraging these methods, the dataset was enriched, enabling the ResNet-50 model to perform significantly better, achieving an impressive classification accuracy of 98.10%. The research highlights the benefits of using the ResNet-50 architecture, which outperformed other models like VGG-16, VGG-19, and Xception. The residual blocks and identity mapping in ResNet-

50 not only enhanced gradient flow but also allowed for deeper network structures without the risk of vanishing gradients. This contributed to improved model robustness, efficient feature extraction, and precise classification of both healthy and diseased rice leaves. In conclusion, this work lays a strong foundation for leveraging AI-driven solutions to address critical challenges in agriculture, enhancing crop health monitoring, and contributing to sustainable farming practices. With further development, the proposed framework has the potential to revolutionize plant disease detection, ensuring better agricultural outcomes and food security.

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