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Paddy Leaf Disease Detection using Deep Learning

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Abstract:-

Paddy leaf disease detection using deep learning refers to training the neural networks on images of paddy leaves to precisely identify diseases. It supports early detection, wrapped in an overall reduction of crop loss, providing windfall to agricultural productivity. The consequences of plant diseases are a significant limitation to agricultural productivity, and monitoring manually is usually cumbersome, unreliable, and time-consuming. The model ORB-DL is used to extract the key features for identifying plant diseases. Combined with advanced DL models, MobileNetV2, ResNet50 these features increase the accuracy and robustness of disease detection. Thermal Imaging is capable of detecting small alterations even before visible symptoms manifest and allows for event-driven management. Grad-CAM visualization techniques provide interpretability results that afford insight into model predictions and build up confidence in automated solutions. Our experiment will show that the combination of ORB-DL with these DL architectures outperforms existing methods while still providing superior accuracy and reliability. The objectives of this study are to employ some of the means of Artificial Intelligence, Deep Learning (DL), and Thermal Imaging in early disease detection and mitigation of shortcomings.

Keywords*:* Paddy Leaf Disease Detection, Deep learning, Precision Agriculture, Computer Vision, Convolutional Neural Network, Plant Disease Diagnosis.

1. Introduction

Rice is the primary food for more than 40 percent of all people around the world, making its production a matter of both national and international importance in food production. Agricultural statistics show rice production that, by 2030, will be at least 1.5 times higher in

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total than at present [1]. However, different challenges such as pests, plant diseases, and the environment have impacted rice yield and quality considerably. Diseases that cause rice yield loss reside in different fungal, bacterial, and viral pathogens, which include rice blast, bacterial leaf blight, brown leaf spot, leaf folder, sheath blight, Hispa, and sheath rot [2],[3]. These diseases may cause approximately 20 percent losses of yield on average, while some outbreaks are even worse, causing over 50 percent losses without early detection [4],[5]. Effective management of diseases, which includes early detection and intervention, is essential for mitigating crop loss and maximizing productivity. Traditionally, the diagnosis relies upon manual visual inspection of rice disease diagnosis, thus exposing them to human error and time-consuming effort. Utilizing deep learning to detect plant diseases can provide the requisite alternative that is both more efficient and accurate. Techniques of both machine learning (ML) and deep learning have been successfully used in agricultural applications for plant disease detection. A variety of approaches towards ML exist, with convolutional neural networks (CNNs) providing the best performance on image-based classification tasks among them. In the present study, the ORB-DL model is used to extract the salient features, and reliable classification is achieved with MobileNetV2 for an improved detection of diseases. Alongside, thermal imaging technology has been another major improvement on the early disease detection front, whereby it can sense minute temperature differences in the infected leaves before the appearance of any visible symptoms. The high contrast imaging of the thermal image sensors, along with their insensitivity to the light conditions of the surroundings, viewpoint within a reasonable distance, and general ability to work in useful weather conditions [6], gives an added weight in the detection of diseases. By combining deep learning with thermal imaging, we're making it much easier for farmers to detect diseases in their crops. This technology not only boosts the accuracy of disease detection but also gives farmers real-time feedback, helping them take action quickly and effectively.

Plant disease identification through ML and DL-based methods is explored in various research studies. While Manoj Mukherjee et al. [7] used histogram techniques for rice disease categorization, Gayathri and Neelamegam [8] leveraged Discrete Wavelet Transform and Grey Level Co-occurrence Matrix for feature extraction. Khaing and ChitSu [9] used Principal Component Analysis (PCA) and color-grid-based statistical features for disease classification using support vector machines (SVMs). More recent approaches include deep learning models, especially CNNs, which have a higher accuracy than traditional ML classifiers like KNN and SVM [10],[11]. Unfortunately, however, most of the time deep learning models require a really good computational resource and feature selection techniques which make the process even faster.

In addition to improving upon deep learning-based classifiers, this research takes an interpretative approach to classification through the application of Gradient-weighted Class

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Activation Mapping (Grad-CAM). Grad-CAM provides visual explanations of the model's predictions, enabling farmers and agricultural experts to trust the result of automated disease detection. Our approach aims to improve upon existing approaches through the combination of ORB-DL feature extraction, MobileNetV2 classification, and thermal imaging for the early detection of diseases to achieve high accuracy and reliability.

2. POWER QUALITY

Paddy leaf disease detection is a crucial research area due to its direct impact on crop yield and food security. Various approaches, including machine learning and deep learning, have been explored to enhance the accuracy of detecting and classifying diseases in paddy leaves. Sachan et al. [1] proposed the idea of using thermal images along with convolutional neural networks (CNNs) for detecting diseases in paddy leaves, hence showing the amazing ability of thermal imaging in disease identification. Sequeira et al. [2] proposed an intelligent system for paddy crop disease detection and prevention using machine learning under the name of Agricare. Prajwalgowda et al. [3] applied ML algorithms to paddy crop disease detection, laying emphasis on feature extraction for enhanced classification precision. Singh et al. [4] adopted digital image processing techniques along with SVM classifiers for the rice disease classification task, thereby showing promising results in disease categorization.

Song et al. [5] used the SVM method for corn leaf disease recognition, thus demonstrating its applicability to plant disease classification. Deng et al. [6] applied deep learning to diagnose rice diseases completely automatically, thereby acknowledging the robustness of CNN-based models. Nalini et al. [7] have performed optimization of deep neural nets for the detection of paddy leaf disease, thereby optimizing the neural network techniques through network optimization that gave great accuracy in the detection performance. The main aim of Saleem et al. [8] was to compare CNN models and deep learning optimizer for plant disease classification along with their strengths and weaknesses regarding various optimization strategies. Ghazi et al. [9] explored deep neural networks and transfer learning for plant identification, optimizing the transfer learning parameters for performance enhancement.

Konar et al. [10] examined various learning rate scheduling techniques in CNNs, displaying the influence of learning rate scheduling on the training of models. Teng [11] discussed the use of neural networks in adaptive control of nonlinear systems, emphasizing adaptivity in neural networks. Schaul et al. [12] proposed several techniques that seem to remove the dependence on learning rate tuning in neural networks, contributing to an optimization of deep learning models.

Simonyan and Zisserman [13] presented very deep convolutional networks for large-scale image recognition, which became the basis for advanced CNN architectures. Sandler et al. [14] proposed MobileNetV2, which is an efficient deep learning model based on inverted residuals

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linear bottlenecks for increased computational efficiency. He et al. [15] proposed deep residual learning for image classification, improving performance in CNNs greatly.

Dong et al. [16] considered multi-operator image resizing techniques that could do great at preprocessing in the image-based disease detection tasks. Dataset available on Kaggle [17] holds thermal images of diseased and healthy paddy leaves, providing an important step for model training and evaluation.

Various levels of infrared radiation released from the plants can be measured through thermal cameras. These cameras are found to be a suitable aid tool in analysing the infected leaf parts It is reported that the emitted radiation can be used to investigate the patterns that are present inside and outside the leaf surfaces. These features are then fed into the models for a deep analysis in order to classify the disease. Thermal imaging provides a considerable significance in prediction due to its high sensitivity. Despite of various existing models, certain enhancements in these techniques are needed to perform the detection more accurately.

3. Methodology

This study presents a deep learning-based approach for early detection of paddy leaf diseases using thermal imaging. By capturing temperature variations in leaves, thermal images help identify disease symptoms before they become visibly apparent, allowing timely intervention. Feature extraction is performed using deep learning models like DenseNet121, MobileNetV2, ResNet50, and VGG16, which analyze patterns in the images. ORB key points further enhance the detection by identifying crucial regions. These extracted features are then used for disease classification, ensuring accurate identification of affected leaves. To improve readability, Grad-CAM generates heatmaps that highlight the regions influencing the model's predictions. This transparency helps farmers and researchers understand the reasoning behind the classifications.

By combining thermal imaging, deep learning, and explainability techniques, this approach offers a reliable solution for detecting paddy leaf diseases early, enabling farmers to take preventive measures and reduce potential crop losses. Feature extraction may include

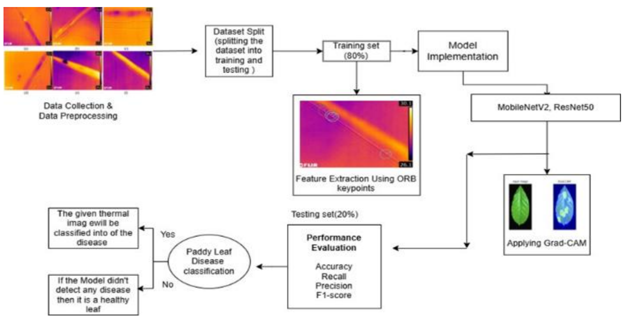

Figure 1: Overview of System Architecture

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Our proposed model for paddy leaf disease detection follows a structured approach, starting with the collection and preprocessing of thermal images. These images capture temperature variations in paddy leaves, helping in the early identification of diseases. The dataset is split into training (80%) and testing (20%) to ensure reliable model evaluation. Feature extraction is performed using ORB keypoints, which help identify critical areas in the images. The extracted features are then processed by deep learning models such as DenseNet121, MobileNetV2, ResNet, Inception, and VGG16 for classification. To improve readability, Grad-CAM is applied to generate heatmap, highlighting the regions influencing predictions.

The model is evaluated based on accuracy, precision, recall, and F1-score to ensure reliable performance. Once validated, it is deployed for real-time detection, classifying leaves as healthy or diseased, including conditions like Hispa, Blast, BLB, Leaf Spot, and Leaf Folder. This system enables early disease detection, aiding farmers in preventive measures.

TABLE I
CLASS DISTRIBUTION OF THERMAL IMAGES

class	No of Thermal Images
Bacterial leaf blight	220
Hispa	142
Leaf spot	80
Blast	67
Leaf folder	34
Healthy	93
Total	636

To enhance model performance, several preprocessing techniques were applied. Noise reduction was performed to eliminate irrelevant thermal distortions, while image resizing ensured uniform dimensions across all samples. Contrast adjustment was used to refine thermal variations, aiding in disease differentiation. Additionally, ORB descriptors were employed for feature extraction, improving disease-specific feature representation.

For model training and evaluation, the dataset was split into 80% for training and 20% for testing. This structured dataset serves as a foundation for developing a non-invasive, thermal imaging-based approach to early paddy leaf disease detection, promoting timely intervention and improved crop health.

Figure 2: Training and Validation of Accuracy of MobileNetV2

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Figure 3: Training and Validation of Accuracy of ResNet50

In Figure 2, Training accuracy, highlighted in blue, quickly reaches near 1.0 and stabilizes, while validation accuracy, in red, begins lower and fluctuates as it increases, likely converging with training accuracy after several epochs. It indicates a good model learning behavior with less overfitting.

In Figure 3, The graph reflects training and validation accuracy with blue and red respectively over epochs. Initially, both are low and, while the training accuracy fluctuates significantly during the training phases, validation accuracy steadily increases. Towards the end of both of these training routines, both stabilizes, showing increased performance of the model.

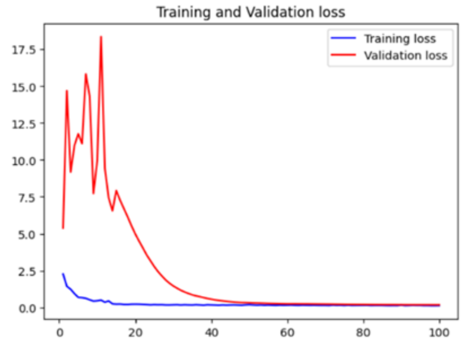

Figure 4: Training and Validation of Loss of MobileNetV2

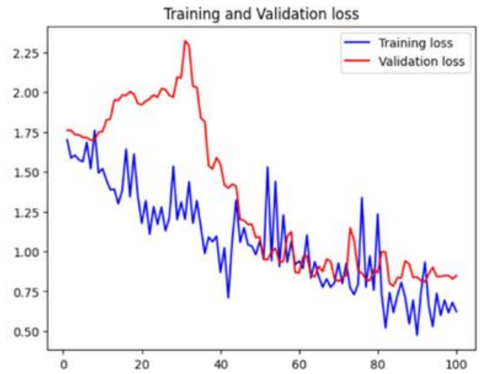

Figure 5: Training and Validation of Loss of ResNet50

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In Figure 4,The training loss, shown in blue, begins at a low value and gradually decreases. The validation loss, indicated in red, starts at a high value, goes through fluctuations, and then steadily decreases toward training loss. Hence, learning in the model was effective, with decreasing error over time.

In Figure 5, The training loss (blue) follows a path that drops gradually but with fluctuations, while the validation loss (red) rises initially, peaks around the 40th epoch, and then declines. The instability followed by convergence suggests some training difficulties but overall learning is progressing.

TABLE II

PERFORMANCE METRICS OF DL MODELS WITH AND WITHOUT ORB

Model Evaluation	Test accuracy	F1 score	Precision	Recall
ResNet50	67.97	0.68	0.70	0.68
MobileNet V2	97.58	0.97	0.97	0.97

The evaluation of our proposed approach indicates that deep learning models are effective in paddy leaf disease detection. MobileNetV2 reached 97.58% accuracy, well over ResNet50, which reached 67.97%. ORB keypoints were used to improve feature extraction by focusing the model on the key disease areas affected. Grad-CAM visualization also added interpretability by enabling the intensively focused comparison of Disease Influencing Regions, further corroborating the trustworthiness of MobileNetV2.

Such confluence of ORB with MobileNetV2 greatly boosts various facets of robustness and accuracy, while with Grad-CAM, explainability is greatly enhanced. This implies that our method is effective in early-stage detection, thereby assisting precision agriculture and promoting a way to avert any potential loss of logistical crops. ORB keypoints were used to extract vital features from paddy leaf images; this allowed effective identification of disease-affected areas.With ORB, feature matching improved and the deep learning model was able to focus on the relevant patterns, improving the accuracy and robustness of disease classification.

This combination of visualization and interpretability not only accounted for transparency in decision-making but also created trust in the automated disease detection system. Or, for the purposes of this goal, the network learned spatial distribution of features related to plants, and it is being used in modern signal-processing applications today.

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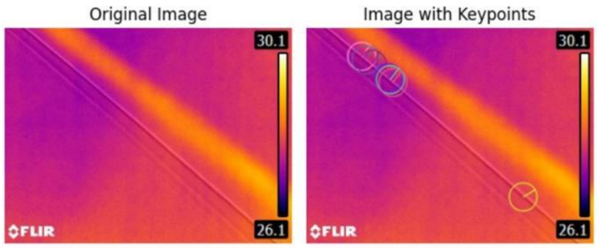

Figure 6: Detecting Keypoints using ORB

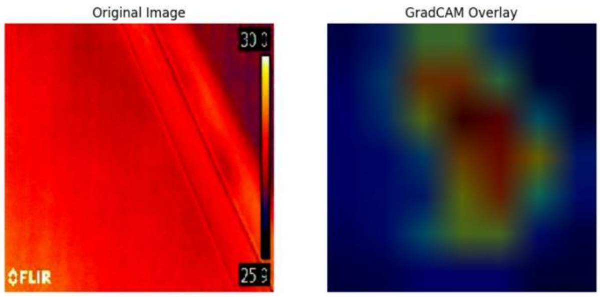

Figure 7: Gra-CAM Image

In Figure 7, the right side presents heatmaps using a color-coded representation to indicate the significance of different regions in the input image for model predictions. On the left side, Grad-CAM visualizations are shown, where heatmaps are overlaid onto the original thermal images. This fusion of heatmaps with input images enhances interpretability, providing insights into key regions influencing the model's decision-making process.

4. Conclusions

Deep learning-based paddy leaf disease detection presents a significant advancement in modern precision agriculture. Traditional manual inspection methods are often labor-intensive, subjective, and inefficient, making automation a necessity. This study integrates ORB-based feature extraction with MobileNetV2 for classification, significantly enhancing accuracy and robustness. The use of thermal imaging enables early disease detection by capturing subtle temperature variations before visible symptoms appear. Additionally, Grad-CAM visualization improves model interpretability, fostering trust in AI-driven predictions.

The results demonstrate that combining ORB feature extraction with deep learning outperforms conventional methods, offering higher precision and reliability. By adopting this approach, farmers can detect diseases early, reducing crop losses and promoting sustainable farming. Future advancements can explore real-time IoT-based monitoring, multi-spectral imaging, and

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cloud deployment to improve accessibility and scalability. AI-driven disease detection systems have the potential to transform agricultural disease management, leading to increased crop yields, food security, and economic benefits for farmers.

5.Future Work

The proposed deep learning-based paddy leaf disease detection system holds significant potential for future advancements. Expanding the dataset to include diverse environmental conditions will enhance the model's generalization, ensuring reliable performance across different field scenarios. The integration of IoT-enabled drones and edge AI can facilitate real-time, automated large-scale disease detection, minimizing manual intervention. As thermal imaging technology advances, the detection of early-stage disease symptoms will improve, enabling timely intervention and reducing crop losses.

Incorporating explainable AI techniques such as Grad-CAM will enhance model transparency, fostering trust among farmers and agricultural experts. Further research can explore lightweight deep learning models optimized for mobile and handheld devices, making disease detection accessible to smallholder farmers. Additionally, integrating multi-modal data from hyperspectral and thermal imaging can improve classification accuracy, providing deeper insights into disease progression. Collaborating with agronomists will help fine-tune AI models for real-world agricultural applications, ensuring practical usability.

The future of paddy disease detection lies in developing an integrated AI-driven ecosystem combining IoT, multispectral imaging, and cloud-based platforms for real-time, high-precision disease monitoring. Expanding this technology to other crops and agricultural sectors, along with integration into government initiatives, can drive sustainable farming, improve food security, and support global agricultural resilience.

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