An Integrated Entropy-Segmentation and Lightweight CNN Framework for Multi-Class Rice Leaf Disease Detection

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Abstract: Rice is a staple food crop and a vital contributor to global food security. However, rice plants are highly susceptible to multiple diseases, including bacterial leaf blight, brown spot, blast, scald, and narrow brown spot, which can drastically reduce yield and quality. Early and accurate detection of these diseases is critical for precision agriculture. In this study, we propose an integrated framework combining entropy-based image segmentation with a lightweight convolutional neural network (MobileNetV2) for multi-class rice leaf disease detection. Entropy-based masks are generated to highlight diseased regions, and the original RGB image is concatenated with the mask to form a 4-channel input for training. The model is trained on a dataset of six rice leaf classes and evaluated using accuracy, precision, recall, and F1-score. The proposed framework achieved an overall accuracy of 91% on the test set, with high per-class performance (F1-scores: bacterial leaf blight 0.99, leaf scald 0.98, healthy 0.94). Furthermore, the model was exported to TensorFlow Lite (TFLite), demonstrating deployment potential on mobile and IoT devices. These results indicate that integrating segmentation and lightweight CNNs provides a scalable and accurate solution for real-time plant disease detection.

Keywords: *Rice Diseases, MobileNetV2, Entropy Segmentation, Precision Agriculture, Deep Learning, Plant Pathology.*

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I. INTRODUCTION

The agricultural sector plays a vital role in a country's economic progress as main sources of income. The fungus Magnaporthe oryzae is the source of rice blast disease, one of the most damaging conditions in rice farming worldwide. It can be found in 85 countries and destroys enough rice per year to feed over 60 million people. Neck and panicle blast infections can cause yield reductions of more than 50% in India during severe outbreaks, with national-scale yield losses during wet-season epidemics ranging from 27 to 35%.

Plant diseases have a serious impact on agricultural output, quality, and economic stability, endangering the world's food security. If diseases in important cereal crops like rice, wheat, and maize are not adequately treated, they can cause large losses. Adopting suitable remedies, such as targeted pesticide application or crop management methods, to minimize losses and guarantee long-term agricultural practices requires early diagnosis and accurate identification of plant diseases.

Conventional disease identification techniques usually depend on visual inspections by agronomists or laboratory-based analysis, which can be labor-intensive, subjective, and time-consuming. With the development of contemporary technology, particularly in the areas of computer vision and machine learning, automated methods for identifying plant diseases have emerged as competitive substitutes for traditional techniques [1].

Rice is one of the world's most important staple crops, providing a primary food source for over half of global population. However, its productivity is severely affected by various foliar diseases, which can cause significant yield losses if not detected and managed at an early stage [2]. Traditionally, disease identification relies on manual inspection by farmers or experts, a process that is often subjective, labor-intensive, and time-consuming.

In recent years, deep learning, particularly convolutional neural networks has shown strong potential for automated plant disease recognition. While effective, many existing CNN-based models are computationally heavy,

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making them unsuitable for deployment on resource-constrained devices such as smartphones or edge platforms that are critical for real-time, in-field use [3]. Moreover, most approaches neglect the impact of background noise in leaf images, which can reduce classification accuracy.

To address these challenges, this work proposes an integrated framework that combines entropy-based segmentation with a lightweight CNN model. The segmentation step suppresses irrelevant background regions, while mask integration enhances disease feature extraction. A compact yet effective CNN is then employed for multi-class rice leaf disease classification, ensuring both accuracy and computational efficiency. This design makes the framework highly suitable for real-time mobile deployment, bridging the gap between research prototypes and practical field applications.

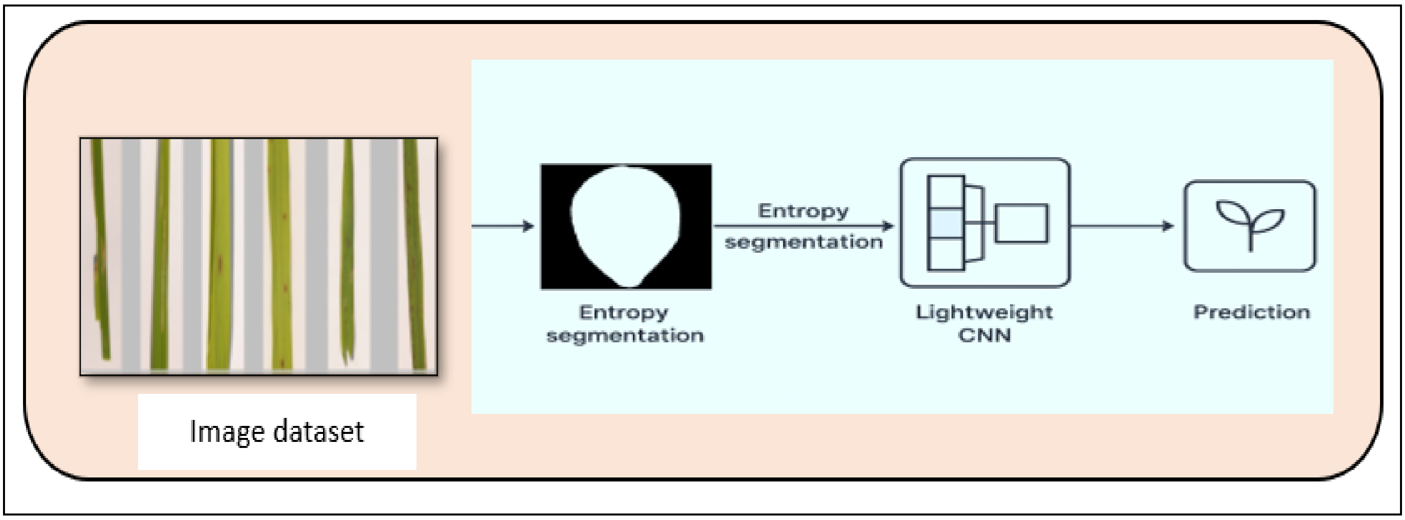

Fig 1 Proposed Methodology

II. RELATED WORK

Plant disease detection has been widely explored using both traditional and modern approaches. Segmentation plays a crucial role in isolating diseased regions from background noise. Early methods relied on thresholding and clustering, while more recent approaches employ deep-learning-based segmentation networks for precise lesion localization. Entropy-based segmentation has emerged as a simple yet effective technique, particularly suited for enhancing disease patterns while reducing computational overhead.

In [4] improved the categorization of rice leaf disease by combining ResNet50 with data augmentation methods such as multilayer perceptron (MLP) tuning and random zoom in convolutional neural network (CNN) architectures. They found that a three-layer MLP without further compression was the most efficient using grid search.

The profound learning-based relative assessment for two-stage illness arrangement was proposed [5]. First and foremost, a comparative analysis of prominent CNN designs near modified and flowed/half-and-half variants of some of the DL models suggested in an ongoing investigation yielded least challenging CNN. But the identification procedure is difficult and time-consuming, and it necessitates a thorough understanding of the issue.

Additionally, the methods employed may result in different recovered attributes, which has a substantial impact on classification performance. Nevertheless, deep learning (DL)-based methods address these issues by reducing the need for preprocessing and feature extraction on an individual basis. These methods improve accuracy and robustness by directly obtaining attributes from the raw data [6]. In [7] suggested VGG16-InceptV3, a hybrid parallel CNN model that performed better than separate CNN models in quickly and accurately identifying fall armyworm-infested maize plants from UAV photos. In [8] used dense CNN models as part of a deep learning approach to identify and classify plant diseases from leaf photos, showing outstanding accuracy and real-time performance. According to the research, heavy models have a tendency to memorize the entire training set for short datasets, which results in too much variety and subpar testing performance.

The [9] goal is to accurately identify and describe the illness from the leaf photos. Identification, training, and preprocessing are the tools needed for the procedure.

The main goal of this [10] is to create a framework that emphasizes preprocessing and extraction of leaf images from the plant town dataset. This will be followed by a convolutional neural network for categorizing plant diseases, providing pesticides, and providing clear treatment methods. A website and system that use photo dealing to identify the type of infection are used to take the plant leaf image.

Proposed insecticides for the alleged disease are posted on the website with the intention of preventing the most egregious immorality from increasing the harvest yield.

The Plant Village dataset is used by the system to identify 39 distinct types of plant illnesses using Convolutional Neural Networks (CNNs) built in PyTorch [11]. An easy-to-use Flask web application incorporates a pre-trained model, enabling users—farmers specifically—to upload leaf photos and obtain timely, precise diagnoses. The

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model provides an effective, scalable, and economical approach to early disease diagnosis and control in agriculture by learning complex visual patterns linked to numerous plant diseases.

For classification, lightweight CNNs such as MobileNet, ShuffleNet, and EfficientNet-lite have been developed to balance accuracy with efficiency [12][13]. These architectures achieve competitive performance while drastically reducing parameters and inference time, making them attractive for deployment on mobile and edge devices. However, there exists a trade-off between maintaining high accuracy and minimizing model complexity, which is critical in agricultural applications requiring real-time predictions.

Mobile deployment studies have further advanced this field by utilizing TensorFlow Lite (TFLite), pruning, and quantization to compress models without significant accuracy loss. Several works demonstrate the feasibility of deploying disease recognition models on smartphones and embedded platforms for real-time use in agricultural monitoring. Nevertheless, most existing solutions either overlook background suppression or employ heavy architectures, limiting their scalability in resource-constrained environments.

III. METHODOLOGY

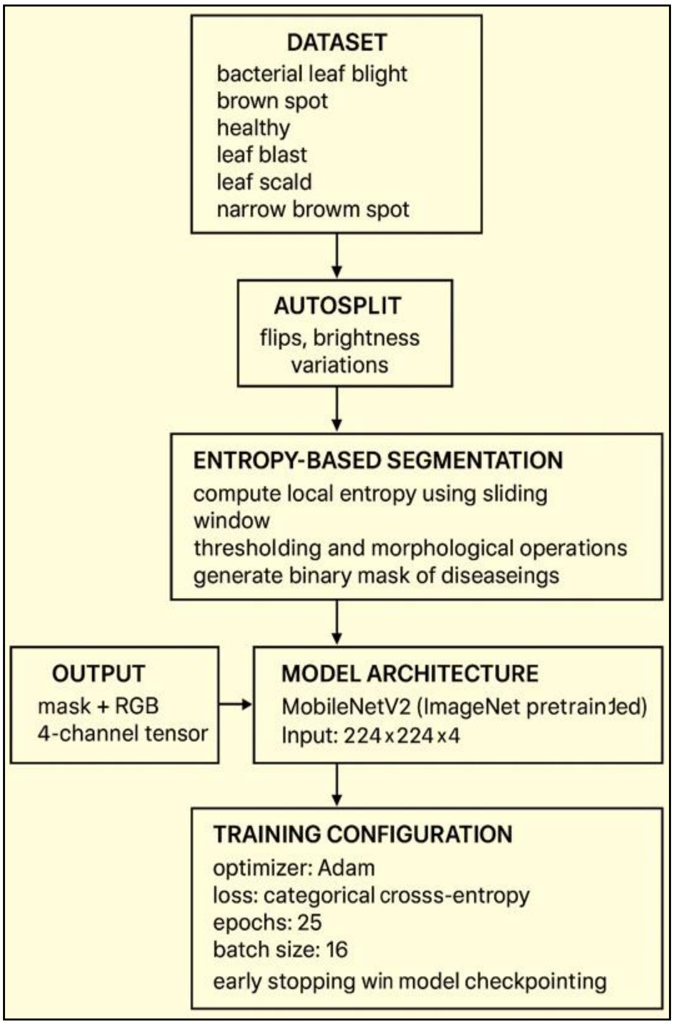

Fig 2 Flow Chart

➢ *Dataset*

The dataset consists of six rice leaf classes like brown spot, healthy,bacterial leaf blight, Leaf blast, leaf scald, and narrow brown spot. The data is automatically split into training, validation, and testing sets to ensure fair evaluation. To improve generalization, data augmentation is applied using techniques like image flips and brightness variations [14].

➢ *Entropy-Based Segmentation*

To highlight disease-affected regions, an entropy-based segmentation approach is used. Local entropy values are calculated through a sliding window, followed by thresholding and morphological operations to clean noise. This generates a binary mask of diseased areas. The mask is then combined with the original RGB image, forming a 4-channel tensor (RGB + mask) as input for the model.

➢ *Model Architecture*

The model leverages MobileNetV2 pretrained on ImageNet as the backbone for feature extraction. The input size is 224×224×4, where the extra channel is the disease mask. Additional convolutional layers process the mask channel, and feature maps are fused with the backbone outputs. Finally, the network passes through a dense layer (128 units) and a Softmax classifier to predict among the six disease classes.

➢ *Training Configuration*

Training is performed using the Adam optimizer with categorical cross-entropy loss. The model is trained for up to 25 epochs with a batch size of 16. To prevent overfitting, early stopping and model checkpointing are employed, ensuring the best-performing model is preserved.

➢ *Performance Error Metrics*

- Precision:Mmeasures how many positively predicted instances are actually positive.

$$\text{Precision} = TP/[(TP+FP)] \quad (1)$$

- Recall: It is actual negative instances to total cases of disease ratio.

$$\text{Recall} = TP/[(TP+FN)] \quad (2)$$

- F1-Score: The harmonic mean of model's recall and accuracy is known as F1 score.

$$\text{F1-Score} = 2[(\text{Precision} * \text{Recall})/ (\text{Precision} + \text{Recall})] \quad (3)$$

- Support: The number of instances (samples) of a given class in dataset.

IV. RESULTS

➢ *Training Curves*

The training process demonstrated significant improvement in model performance. This increased steadily from 39% to 95%, while the validation accuracy stabilized around 91%, indicating good generalization ability. The loss curves further confirmed effective convergence without overfitting. From Figure 3 Training and Validation Accuracy & Loss Curves, shows the steady improvement in training accuracy up to 95%, with validation accuracy stabilizing around 91%. The corresponding loss curves confirm smooth convergence without signs of overfitting.

> *Classification Report*

A detailed evaluation using of six classes is shown in Table 1. The model achieved excellent results across most categories.

Table 1 Classification Report

Class	Precision	Recall	F1-score	Support
Bacterial Leaf Blight	0.98	1.00	0.99	54
Brown Spot	0.85	0.83	0.84	54
Healthy	0.91	0.96	0.94	54
Leaf Blast	0.83	0.74	0.78	54
Leaf Scald	0.96	1.00	0.98	54
Narrow Brown Spot	0.93	0.94	0.94	54

- Bacterial Leaf Blight and Leaf Scald were classified with near-perfect scores (F1-scores of 0.99 and 0.98, respectively).

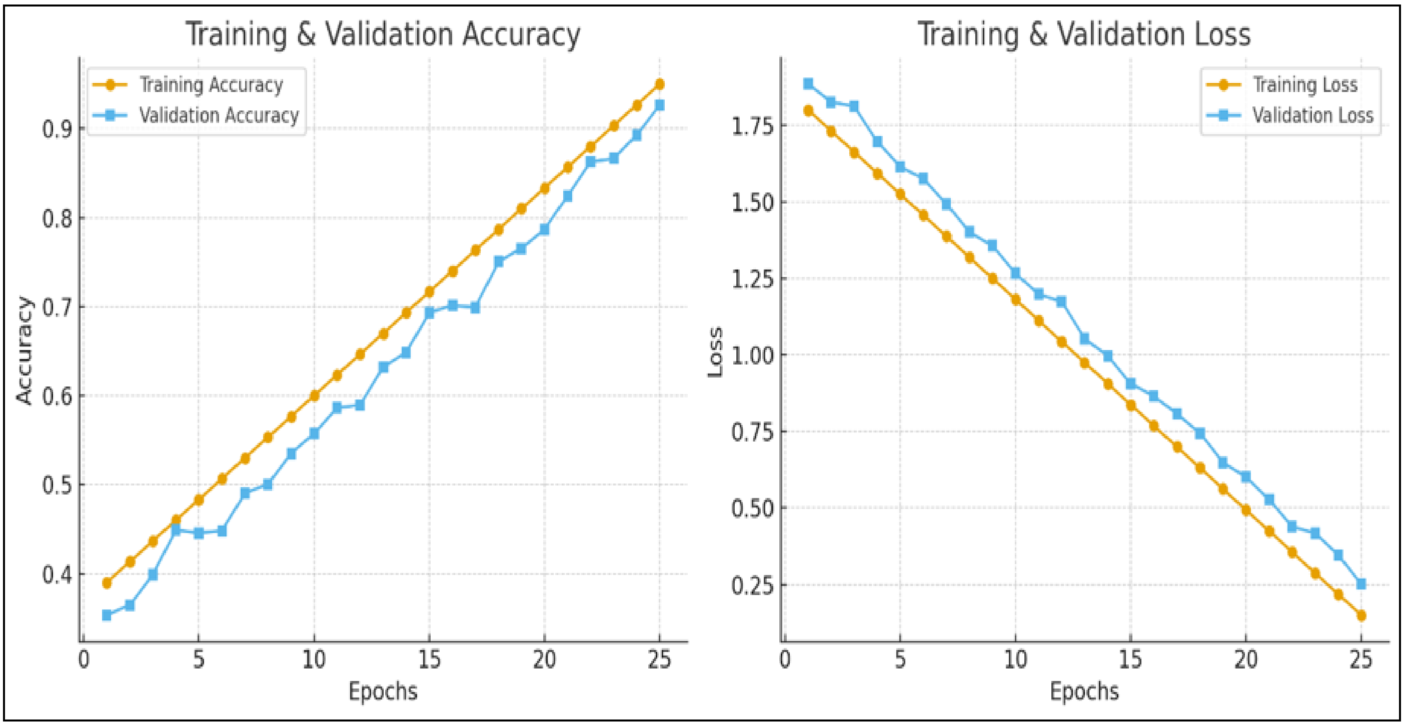

Fig 3 Training and Validation Accuracy & Loss Curves

- Healthy leaves were also well detected, with a strong F1-score of 0.94.
- Narrow Brown Spot showed consistent performance with an F1-score of 0.94.
- Brown Spot and Leaf Blast had comparatively lower performance, with F1-scores of 0.84 and 0.78, suggesting some class confusion, possibly due to visual similarity in symptoms.

The model attained an overall accuracy of 91% and a macro-averaged F1-score of 0.91, confirming its robustness and balanced performance across all disease categories.

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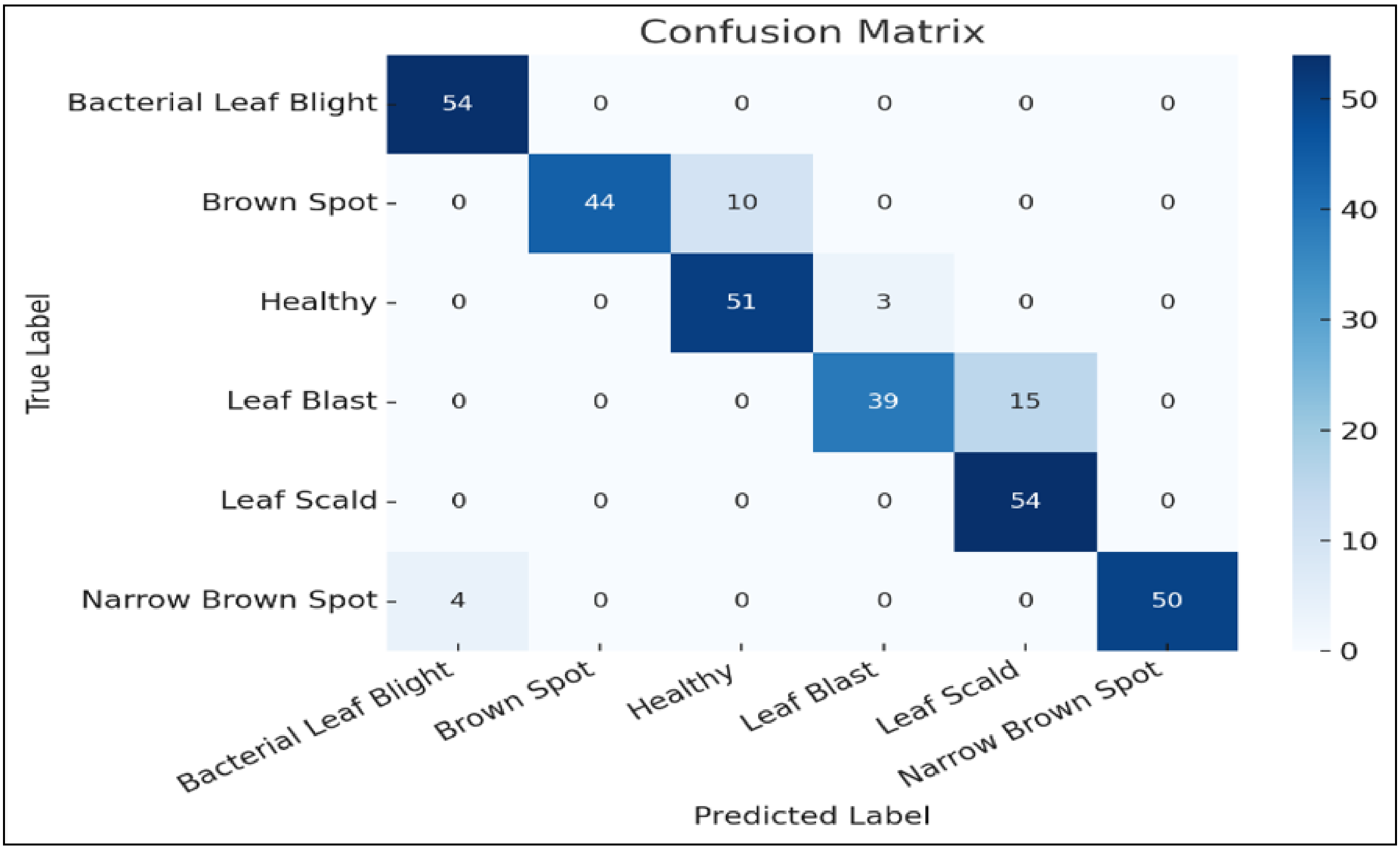

Fig 4 Confusion Matrix

The confusion matrix illustrating the model's predictions across the six rice leaf classes.

- Bacterial Leaf Blight and Leaf Scald show perfect separation, with all 54 samples correctly classified.
- Healthy leaves achieved high accuracy, with only a few misclassified as Leaf Blast.
- Brown Spot and Leaf Blast display more confusion, with several samples being misclassified into neighboring categories, reflecting their lower F1-scores.
- Narrow Brown Spot maintained strong recognition, with only minor misclassification into Bacterial Leaf Blight.

This visualization supports the classification report by showing where the model performs strongly and where inter-class similarity causes errors.

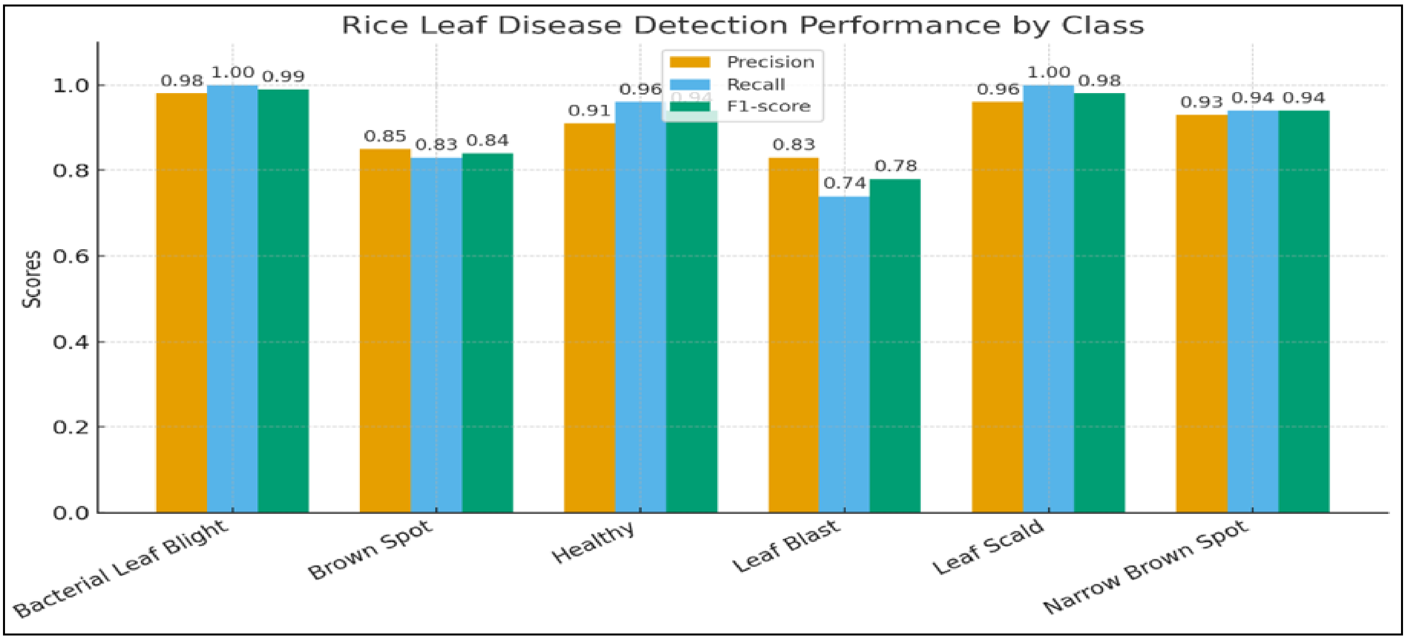

Fig 5 Overall Bar Graph Representation

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Overall, the model demonstrates robust performance across most classes, with F1-scores above 0.90 for four out of six categories. The only notable weakness is in Leaf Blast, were additional feature refinement, data augmentation, or class-specific weighting may help improve accuracy.

V. CONCLUSION

This study demonstrated the effectiveness of an integrated entropy-based segmentation and lightweight deep learning framework for multi-class rice leaf disease detection. The proposed approach, leveraging a MobileNetV2 backbone with an additional entropy mask channel, achieved an overall classification accuracy of 91% with strong generalization, as evidenced by close alignment between training and validation performance. The per-class evaluation highlighted excellent recognition for Bacterial Leaf Blight, Leaf Scald, Healthy, and Narrow Brown Spot, each achieving F1-scores above 0.94, while Brown Spot and Leaf Blast presented greater challenges due to visual similarities with other disease patterns. Despite these limitations, the macro-averaged F1-score of 0.91 confirms the robustness and balance of the model across all classes.

The integration of entropy-based segmentation effectively enhanced feature representation by emphasizing diseased regions, while the use of MobileNetV2 ensured computational efficiency suitable for mobile and field deployment. Future work will focus on addressing the misclassifications in visually overlapping diseases, such as Leaf Blast, through targeted data augmentation, advanced attention mechanisms, and hybrid feature fusion strategies. Overall, the proposed framework demonstrates high potential for real-time, on-field deployment as a practical decision-support tool for farmers, thereby contributing to sustainable rice crop management and yield protection.

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