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Classification of Paddy Leaf Diseases using Deep Learning

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Abstract—In recent years, paddy leaf diseases have posed a significant threat to rice crop yield and quality. This study presents a deep learning-based classification model utilizing EfficientNetB5 to detect and categorize common paddy leaf diseases. The proposed model automates the disease diagnosis process with high precision and improved computational efficiency. Image preprocessing techniques such as resizing, normalization, and noise removal are applied to enhance feature extraction. The model is trained and validated on a curated dataset of diseased paddy leaves. Results indicate superior performance in terms of accuracy, precision, and recall compared to existing CNN based models. While the objective is met effectively, limitations such as computational demand and the need for broader dataset diversity remain. These are discussed in the related work section.

Index Terms—Paddy Doctor dataset, Plant disease classification, EfficientNet-B5, Deep learning, Image-based diagnosis.

I. Introduction

Food is fundamental to life, and among the staple crops that feed billions, rice holds a central role in ensuring global food security. India, being the second-largest producer and a top exporter of rice, plays a vital part in meeting this demand. Over the decades, the country's rice production has seen remarkable growth—rising from around 53.6 million tons in 1980 to over 120 million tons by 2020–21, with recent estimates suggesting a further increase to 130.8 million tons in 2022–23 [1].

States like West Bengal, Uttar Pradesh, Punjab, Odisha, Andhra Pradesh, and Tamil Nadu are at the forefront of this agricultural achievement, collectively contributing around 72% of India's total rice output. Despite this progress, traditional farming practices are still prevalent, and farmers often face serious challenges—particularly from crop diseases that can significantly affect both the yield and quality of rice.

One of the most destructive of these is *rice blast disease*, caused by the fungal pathogen *Magnaporthe oryzae*. It spreads rapidly under the right environmental conditions and leaves behind distinctive diamond-shaped lesions with gray centers and dark brown borders on rice leaves, stems, and panicles [2]. In severe cases, it can lead to neck blast, where panicles become sterile, resulting in total crop failure [3]. Such losses not only affect farmers' incomes but also pose risks to food availability and prices.

To combat this, early disease detection is critical. In recent years, the integration of advanced technologies in agriculture has paved the way for automated plant disease detection. Unlike traditional manual inspections, these modern systems offer faster, more accurate, and scalable solutions. Deep learning models like ResNet, DenseNet, and EfficientNet have been especially promising for plant disease classification. ResNet addresses vanishing gradients through residual connections, DenseNet promotes feature reuse by densely linking layers, and EfficientNet introduces a clever scaling method that balances depth, width, and resolution to optimize model performance [4].

Among these, EfficientNet-B5 stands out for its ability to extract complex patterns while maintaining computational efficiency. By smartly adjusting network parameters, it delivers high accuracy with fewer resources [5]. In this study, we enhance EfficientNet-B5 by incorporating Swish activation

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layers, aiming to further boost its ability to classify paddy leaf diseases accurately [6].

II. RELATED WORKS

Deep learning techniques have revolutionized agricultural disease management, especially in paddy farming where timely disease detection significantly impacts yield and quality. Several studies have explored deep learning architectures, with the EfficientNet family gaining particular attention for its accuracy and efficiency.

In [6] implemented EfficientNet B4 on the Paddy Doctor dataset and achieved 99.09% training accuracy and 96.91% testing accuracy . Its success is attributed to compound scaling and the Swish activation function, which enhance feature extraction while preserving computational efficiency.

A comparative analysis between EfficientNet B4 and B5 revealed that B5 performed better on augmented datasets, indicating that deeper architectures can effectively capture complex patterns [7]. EfficientNet B3 has also been successfully applied to rice leaf disease classification and segmentation, showing strong visual recognition capabilities in agricultural settings [8]. Furthermore, EfficientNet B6 outperformed several other deep learning models in sugarcane disease detection, highlighting its effectiveness and adaptability for various crop monitoring tasks [9].

Fusion and ensemble models also gained traction. A deep learning-based fusion model named EDLFM-RPD integrated preprocessing, segmentation, feature extraction, and classification stages, achieving 96.17% accuracy across three disease types [10].

Optimization strategies have enhanced model performance. One approach used a Deep Neural Network optimized via the Crow Search Algorithm (CSA), improving both accuracy and computational efficiency for multiple rice diseases [11]. Bi and Wang introduced attention mechanisms within CNNs (including EfficientNet), which improved lesion area detection [12].

Various implementation methods have also emerged. One used Raspberry Pi for data storage and smartphones for image capture, making AI-based detection accessible to farmers [13]. Another used thermal imaging and machine learning to extract features for classifying leaf diseases [14].

In comparison, EfficientNet B4 achieves a slightly higher testing accuracy (96.91%) than EDLFM-RPD (96.17%) and CNN ensemble models (95.54%). EfficientNet's compound scaling balances accuracy and computation, which is vital in field conditions. Meanwhile, fusion and thermal imaging methods offer complementary advantages, especially for early-stage detection.

Future directions include exploring higher EfficientNet variants (e.g., B6, B7), multimodal approaches combining visual and thermal data, edge computing adaptations for realtime detection, and models optimized for early symptom identification.

III. DATASET SPECIFICATIONS

TThe dataset, known as *Paddy Doctor*, is publicly available on Kaggle [15]. It consists of 10 classes — 9 representing various paddy leaf diseases and 1 for healthy leaves. The dataset is composed of real-world field images. It was split in an 80:20 ratio for training and testing, as illustrated in Fig 1.

IV. METHODOLOGY

This study introduces a human-centered, deep learningbased framework aimed at accurately detecting and classifying various paddy leaf diseases. The approach is designed not only to achieve high classification performance but also to address practical challenges commonly faced in agricultural environments. The entire methodology, outlined in Fig. 2, progresses through multiple stages, beginning with image preprocessing and augmentation, followed by model design, training, and interpretive performance evaluation. The solution is designed for real-world farming scenarios, supporting farmers and agricultural experts in disease diagnosis.

A. Dataset Acquisition and Preprocessing

The dataset utilized in this study is sourced from the publicly available Paddy Doctor dataset, which comprises highresolution images of paddy leaves in ten categories—nine diseased classes (Leaf Blight, Leaf Streak, Panicle Blight, Blast, Brown Spot, Dead Heart, Downy Mildew, Hispa, and Tungro) and one healthy class. An 80:20 split was applied for training and validation. All images were resized to 224×224 pixels to ensure consistency and compatibility with model input.

Preprocessing steps included normalization of pixel values to the [0, 1] range to stabilize training and reduce the impact of environmental factors such as lighting and camera settings.

B. Data Augmentation Strategy

To address limited labeled data and reduce overfitting, a data augmentation pipeline was used. Transformations such as horizontal flips, rotations (up to 10°), and brightness adjustments simulate real-world variability. This enhances generalization by enabling the model to learn invariant features across diverse field conditions.

C. Model Architecture

The EfficientNetB5 model, known for its balanced scaling of depth, width, and resolution, serves as the backbone. Pretrained on ImageNet, the model was fine-tuned to adapt to paddy leaf disease classification. The first 200 layers were frozen to retain general features, while the remaining layers were trainable. A one-dimensional feature vector was extracted at this stage.

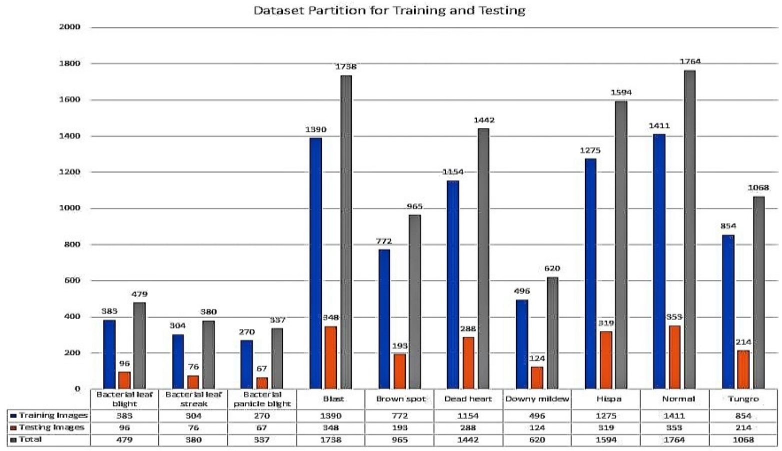

Fig. 1. Dataset Partition

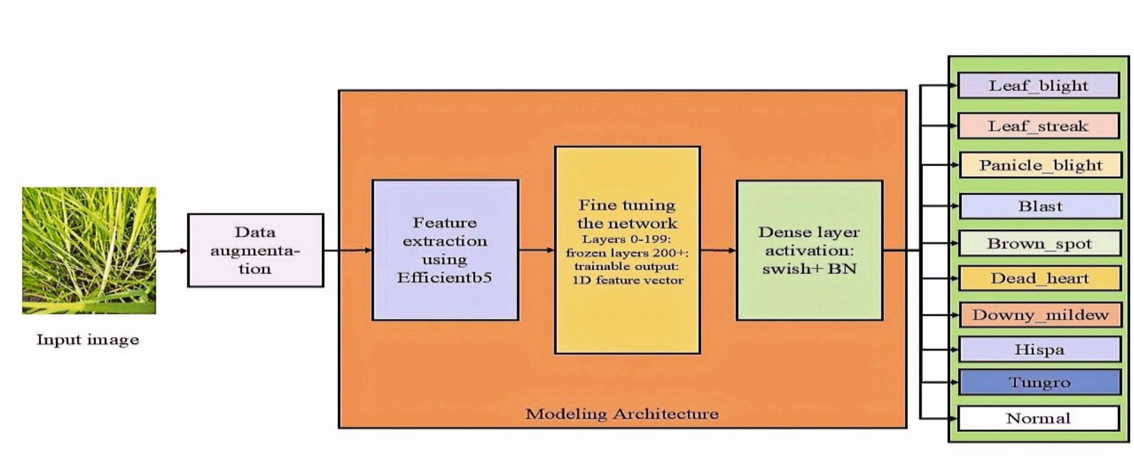

Fig. 2. Block Diagram

D. Dense Classification Head with Swish Activation

The feature vector was passed through fully connected dense layers activated by the Swish function, known for better gradient flow than ReLU. Batch Normalization followed each layer to stabilize training. The final output layer used softmax activation over ten classes, providing interpretable probabilitybased predictions.

E. Model Training and Optimization

Training was conducted using the Adam optimizer with a learning rate of 0.0001. Sparse categorical cross-entropy was used as the loss function. EarlyStopping (patience=6) and ReduceLROnPlateau callbacks helped avoid overfitting and adjust learning rates dynamically. Training ran for up to 50 epochs with a batch size of 32. Metrics were logged continuously.

F. Performance Evaluation

Post-training, the model was evaluated using accuracy, precision, recall, and F1-score metrics. A confusion matrix was constructed to assess classification reliability across classes. Class-wise metrics provided insights into per-disease performance. A classification report further detailed strengths and weaknesses.

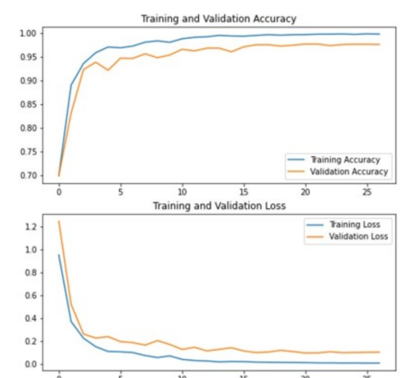

Fig. 3. Training and validation accuracy and loss curves.

The model was also tested on an unseen dataset to simulate real-world conditions. Predictions were analyzed qualitatively and quantitatively to confirm interpretability and decision consistency.

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G. Visualization of Results

Visual tools including line plots, heatmaps, and bar charts aided in analyzing training behavior and classification performance. Seaborn was used for clarity and aesthetic value. These visualizations supported both technical evaluation and communication with stakeholders.

H. Discussion and Interpretation

The model performed well across all ten classes, particularly excelling in detecting distinct diseases like Hispa and Tungro. Misclassifications, especially between visually similar diseases like Brown Spot and Dead Heart, indicated areas for enhancement.

Incorporating multimodal data such as geolocation or climate conditions could further improve classification reliability. Overall, the model offers a scalable and efficient solution for automated paddy disease diagnosis, contributing to the development of precision agriculture systems.

V. RESULTS

The proposed model was validated on an independent set of paddy leaf images representing all ten classes, including both healthy and diseased states such as Leaf Blight, Tungro, and Brown Spot. The model demonstrated robust performance, achieving consistently high classification accuracy.

The confusion matrix (Fig.4) illustrates strong inter-class discrimination, with only minor misclassifications observed, particularly between visually similar diseases like Dead Heart and Brown Spot. The class-wise accuracy distribution (Fig.5) confirms that while most classes achieved near-perfect recognition, a few exhibited slightly reduced precision due to overlapping visual characteristics.

Training metrics (Fig. 3) reflect stable learning dynamics, with validation accuracy consistently improving and stabilizing beyond 95% by epoch 40. This indicates successful mitigation of overfitting through early stopping and learning rate adjustments.

Example predictions (Fig. 6) showcase the model's capability to discern fine-grained differences in leaf texture, color, and shape—further validating its effectiveness in real-world conditions.

The use of EfficientNetB5, augmented by Swish activation and selective fine-tuning, contributed significantly to improved feature extraction. In addition, batch normalization and a comprehensive augmentation pipeline enhanced the model's robustness and generalization.

To contextualize the performance, Table I compares the proposed approach with existing models. Unlike earlier methods that often utilized limited class diversity and images captured in controlled environments, our model excelled in field-image scenarios with a broader disease spectrum. This underlines its practical suitability for on-device deployment in mobile or IoT-based agricultural support systems.

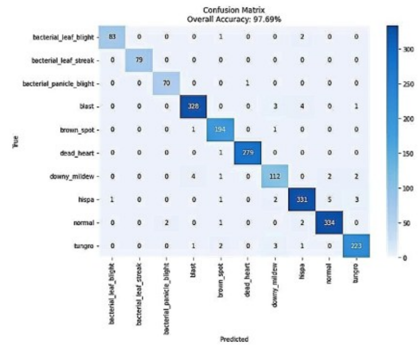

Fig. 4. Confusion matrix showing the classification performance across ten paddy disease classes

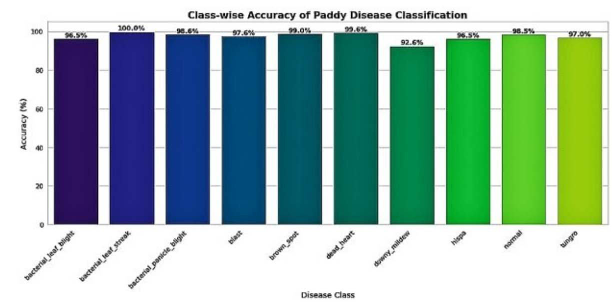

Fig. 5. Class-wise accuracy distribution for the ten disease categories

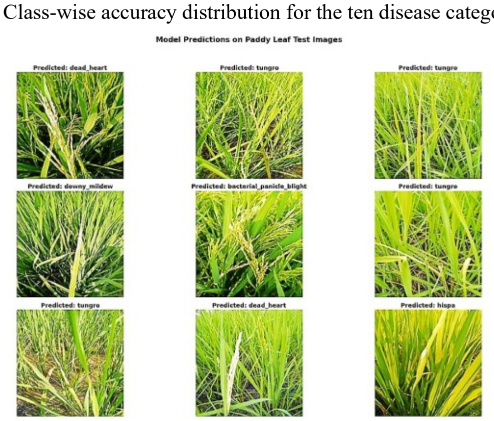

Fig. 6. Sample predictions showcasing input images and their correctly predicted disease labels

TABLE I

PERFORMANCE COMPARISON OF TRADITIONAL AND PROPOSED MODELS IN PADDY LEAF DISEASE CLASSIFICATION

References	No. of class	Type of Images	Adapted methodology	Accuracy
[16]	5 classes	Processed Images	Hybrid feature selection technique and deep learning algorithm	98.86%
[17]	10 classes	Field images	Vision Transformer	97%
[18]	5 classes	Field images	Weighted deep ensemble learning	96%
[19]	5 classes	Field images	SqueezeNet with neural network classifier	93.3%
[20]	5 classes	Field images	ResNet50 plus SVM performs better with F1 score of 0.9838	98.38%
[6]	10 classes	Field Images	Efficientb4	96.91%
Proposed Method	10 classes	Field Images	Efficientb5 with compound scaling and swiss activation	97.69%

In summary, the model not only outperformed many stateof-the-art techniques but also demonstrated high real-world applicability, making it a strong candidate for integration into smart farming solutions.

VI. CONCLUSION

This study establishes the proposed EfficientNetB5-based model as a high-performing solution for paddy leaf disease classification. Achieving an accuracy of 97.69%, it significantly surpasses existing EfficientNetB4 models, which typically reach 96% accuracy. This improvement underscores EfficientNetB5's enhanced feature extraction capability due to compound scaling and advanced activation.

Notably, the model excels in identifying distinct diseases like Leaf Blight and Hispa, while modest challenges remain with diseases such as Downy Mildew and Dead Heart—possibly due to symptom similarity. This reveals opportunities for further enhancement through data augmentation, targeted rebalancing, or the incorporation of multimodal features. The overall framework demonstrates real-world viability through high accuracy, generalization, and adaptability to diverse image conditions. These strengths position the model as a reliable, scalable candidate for integration into precision agriculture platforms, particularly for real-time deployment in mobile or IoT-based solutions.

REFERENCES

[1] "Top 10 rice-producing states in india 2024." Rice News Today, 2024.
[2] "Magnaporthe oryzae." Wiki Bugwood, 2023.
[3] "Rice blast disease." University of Missouri Extension, 2023.
[4] U. Bhattacharya, P. Kumar, and B. Singh, "Deep learning-based plant disease detection: A review," *Archives of Computational Methods in Engineering*, pp. 1–16, 2020.
[5] Q. T. Lu, "An approach for classification of diseases on leaves," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 10, 2023.
[6] J. Padhi, L. Korada, A. Dash, P. K. Sethy, S. K. Behera, and A. Nanthaamornphong, "Paddy leaf disease classification using efficientnet b4 with compound scaling and swish activation: A deep learning approach," *IEEE Access*, 2024.
[7] U. Atila, M. Uc¸ar, K. Akyol, and E. Uc¸ar, "Plant leaf disease classifi-¨ cation using efficientnet deep learning model," *Ecological Informatics*, vol. 61, p. 101182, 2021.
[8] F. Mashroor, I. F. Ishrak, S. M. Alvee, A. Jahan, M. N. I. Suvon, and S. Siddique, "Rice paddy disease detection and disease affected area segmentation using convolutional neural networks," in *TENCON 20212021 IEEE Region 10 Conference (TENCON)*, pp. 891–896, IEEE, 2021.
[9] ˙I. Kunduracıoglu and˘ ˙I. Pac¸al, "Deep learning-based disease detection in sugarcane leaves: Evaluating efficientnet models," *Journal of Operations Intelligence*, vol. 2, no. 1, pp. 321–235, 2024.
[10] A. S. Almasoud, A. Abdelmaboud, T. A. E. Eisa, M. A. Duhayyim, A. A. H. Elnour, M. A. Hamza, A. Motwakel, and A. S. Zamani, "Artificial intelligence-based fusion model for paddy leaf disease detection and classification," *Computers, Materials and Continua*, vol. 72, no. 1, pp. 1391–1407, 2022.
[11] M. Kumar, A. Verma, and R. Singh, "A novel method for detecting diseases in rice plants using a deep neural network optimized with the crow search algorithm," *Computers and Electronics in Agriculture*, vol. 193, p. 106642, 2022.
[12] Y. Bi and J. Wang, "Integration of attention mechanisms with cnn architectures for agricultural disease detection," *Agricultural Informatics Journal*, vol. 13, no. 2, pp. 45–53, 2022.
[13] R. Dodda, S. Maddhi, K. Ambika, S. Kumar, K. Neelima, and M. S. Rani, "Automated plant disease detection and prevention using raspberry pi and cnn algorithm," in *2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC)*, pp. 806–811, IEEE, 2024.
[14] O. Attallah, "Deep learning-based model for paddy diseases classification by thermal infrared sensor: An application for precision agriculture," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 10, pp. 779–784, 2023.
[15] R. Salvatorelli, "Paddy doctor dataset." https://www.kaggle.com/datasets/ricardosalvatorelli1/paddydoctor, 2022.

[16] A. Geetha and N. Prakash, "Classification of glaucoma in retinal images using efficientnetb4 deep learning model.," *Computer Systems Science & Engineering*, vol. 43, no. 3, 2022.

[17] R. K. Dubey and D. K. Choubey, "An efficient adaptive feature selection with deep learning model-based paddy plant leaf disease classification," *Multimedia Tools and Applications*, vol. 83, no. 8, pp. 22639–22661, 2024.

[18] R. S. Jesie, M. G. Premi, and T. Jarin, "Comparative analysis of paddy leaf diseases sensing with a hybrid convolutional neural network model," *Measurement: Sensors*, vol. 31, p. 100966, 2024.

[19] K. Bathe, N. Patil, S. Patil, D. Bathe, and K. Kumar, "Convdepthtransensemblenet: An improved deep learning approach for rice crop leaf disease classification," *SN computer science*, vol. 5, no. 4, p. 436, 2024.

[20] A. Kaur, K. Guleria, and N. K. Trivedi, "A deep learning-based model for biotic rice leaf disease detection," *Multimedia Tools and Applications*, pp. 1–27, 2024.