

Precision Farming with AI: An Integrated Deep Learning Solution for Paddy Leaf Disease Monitoring

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Abstract—Paddy rice, an essential food source for millions, is highly susceptible to various leaf diseases that threaten its yield and quality. This study introduces a cutting-edge hybrid deep learning model designed to address the critical need for accurate and timely identification and classification of paddy leaf diseases. Traditional methods often lack the precision and efficiency required for effective disease detection, necessitating the development of more sophisticated approaches. Our proposed model leverages the feature extraction capabilities of EfficientNetB0 and the hierarchical relationship capturing abilities of the Capsule Network, resulting in superior disease classification performance. The hybrid model demonstrates outstanding accuracy, achieving 97.86%, along with precision, recall, and F1-scores of 97.98%, 98.01%, and 97.99%, respectively. It effectively differentiates between diseases such as Narrow Brown Spot, Bacterial Leaf Blight, Leaf Blast, Leaf Scald, Brown Spot, and healthy leaves, showcasing its robustness in practical applications. This research highlights the importance of advanced technological interventions in agriculture, providing a scalable and efficient solution for disease detection in paddy crops. The hybrid deep learning model offers significant benefits to farmers and agricultural stakeholders, facilitating timely disease management, optimizing resource use, and improving crop management practices. Ultimately, this innovation supports agricultural sustainability and enhances global food security.

Keywords—Paddy rice; leaf diseases; hybrid deep learning; efficientnetb0; capsule network

I. INTRODUCTION

Paddy rice, often referred to simply as "paddy," denotes the raw, unhulled grains of rice, encased within their protective husks. Cultivated extensively across the globe, particularly in regions with flooded fields conducive to rice growth, such as Asia, paddy forms the backbone of numerous cuisines and diets. Boasting a diverse array of varieties, paddy rice encompasses a spectrum of characteristics, from grain size and color to taste and texture. Its cultivation entails meticulous processes, including land preparation, seed selection, and often, transplanting into flooded paddy fields. Rich in carbohydrates and supplemented by proteins, fiber, and various nutrients, paddy rice serves as a vital source of nutrition for a substantial portion of the whole population [1]. Post-harvest, paddy undergoes processing to yield different rice types, from polished white grains to nutrient-rich brown rice variants. This processed rice, in its myriad forms, finds its way into an extensive array of culinary creations, from simple staples to intricate delicacies like sushi and biryani. Economically, rice cultivation and trade represent a cornerstone of many nations' economies, supporting millions of livelihoods and playing a vital role in food security and economic stability. Thus, paddy rice stands as not only a dietary staple but also a

symbol of cultural heritage, economic vitality, and agricultural resilience.

Paddy leaf diseases present a formidable challenge to rice cultivation globally, encompassing a spectrum of fungal, bacterial, and viral pathogens that afflict the leaves of the rice plant. These diseases manifest through a variety of symptoms including lesions, spots, discoloration, and wilting, ultimately impairing the plant's ability to photosynthesize effectively and thereby compromising yield and quality. Spread through diverse vectors such as wind, water, contaminated seeds, and insect carriers, the transmission of these diseases is facilitated by environmental factors like temperature, humidity, and cultural practices [2]. Combatting paddy leaf diseases requires a multi-faceted approach involving cultural, chemical, and biological strategies. Farmers employ techniques like crop rotation and the use of disease-resistant varieties alongside chemical treatments and biological control agents to mitigate disease spread and severity.

The spectrum of paddy leaf diseases includes bacterial leaf blight, leaf blast, brown spot, leaf scald, and narrow brown spot. Bacterial leaf blight, caused by *Xanthomonas oryzae* pv. *Oryzae*, leads to water-soaked lesions and plant wilting. Brown spot, from *Cochliobolus miyabeanus*, shows small lesions with yellow halos. Leaf blast, by *Magnaporthe oryzae*, produces lesions shaped like diamonds with gray centers. Leaf scald, caused by *Rhizoctonia oryzae*, results in elongated, pale streaks on leaves. Narrow brown spot, linked to *Cercospora jansena*, shows elongated brown lesions with yellow borders [3]. And a healthy foliage exhibits vibrant green coloration and intact leaf structure. Vigilant monitoring and management strategies are crucial for mitigating these conditions and ensuring crop productivity and food security.

Paddy leaf disease detection and recognition hold importance in modern agricultural practices for several compelling reasons. Firstly, early detection allows for timely intervention, which is pivotal in curbing the spread of diseases and minimizing crop damage. By swiftly identifying diseased plants, farmers can implement targeted control measures, thereby mitigating yield losses and preserving crop quality. Moreover, accurate disease detection facilitates precision agriculture, enabling farmers to adopt site-specific management practices tailored to the needs of individual fields [4]. This approach optimizes resource utilization, reduces input costs, and minimizes environmental impact. Staying ahead of disease outbreaks optimizes yields and enhances food security, vital for rice-dependent communities. Technological advancements aid research into disease dynamics and resilient crop development. Accurate disease detection is essential for sustaining

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productivity and fostering eco-friendly farming. The important contribution of this study is given below:

- To create a robust model for detecting paddy leaf diseases utilizing a hybrid deep learning approach.
- To effectively identifies and classifies multiple paddy leaf diseases.
- To minimize error rates and false positive occurrences in the detection process.
- To evaluate and contrast the efficacy of the proposed method with existing models for detecting paddy leaf diseases.
- To support for Sustainable Agriculture

The remaining of the paper is structured as: Section II provides an overview of existing methodologies for detecting paddy leaf disease, laying the foundation for the proposed research. Section III outlined the method details of the proposed approach. The outcomes of the study, including the efficiency of the suggested approach in detecting diseases, are discussed in Section IV. At last, Section V offers remarks summarizing the findings and implications of our work.

II. LITERATURE REVIEW

Kulkarni and Shastri [5] emphasized the significance of early diagnosis by outlining a methodical strategy to use machine learning for paddy leaf disease identification. Training a convolutional neural network (CNN) based on the VGG-16 model involved preprocessing methods using a Kaggle dataset. After training, a successful model was obtained with an accuracy rate of 95%. A hybrid CNN model was introduced by Jesie et al. [6] for the categorization of paddy leaf diseases. The hybrid CNN model performed better than other techniques such as Deep Neural Network (DNN), Deep Belief Neural Network (DBN), and Recurrent Neural Network (RNN). Notable outcomes included accuracy of 97%, under 5% error, F-measure of 92.3%, 93.1% precision, 92.1% recall value.

Trinh et al. [7] detailed a methodology for detecting paddy leaf diseases by the YOLOv8 model, focusing on leaf folder, leaf blast, and brown spot. It collected a dataset of 1634 images from rice fields at the Vietnam National University of Agriculture with data augmentation techniques applied for improved model adaptability. The YOLOv8n architecture was chosen for its balance of accuracy, speed, and efficiency, with modifications to the loss function incorporating Efficient IoU (EIoU) and Alpha-IoU to enhance bounding box regression. Parameter settings were optimized to achieve high precision (89.6), recall (83.5), F1-score (86.4), and mAP (88.9) during model training. Evaluation showed significant improvements over the baseline YOLOv8 model, with enhancements in accuracy across disease classes.

Bi and Wang [8] presented a method for paddy leaf disease detection using a double-branch DCNN (DBDCNN) model integrated with a convolutional block attention module (CBAM). The methodology involved training the DBDCNN model on a dataset comprising annotated rice leaf images. Also compared the performance of the model with established ones like VGG-16, ResNet-50, and MobileNet-V2. Results showed

the model achieved a remarkable accuracy of 97.73%, surpassing all comparative models. This high accuracy underscores its potential for accurate disease classification in agricultural settings.

Bharanidharan et al. [9] used a Modified Lemurs Optimization (MLO) Algorithm as a filter-based feature transformation technique to increase the efficiency of recognizing different paddy diseases in thermal pictures of paddy leaves. The authors created the proposed Modified Lemurs Optimization Algorithm by modifying the original Lemurs Optimization, taking influence from the Sine Cosine Optimization. Studying 636 thermal photos of both healthy and sick paddy leaves is part of the analysis. Four machine learning methods are evaluated: the RF, the Linear Discriminant Analysis, the K-Nearest Neighbor, and the Histogram Gradient Boosting. At first, these classifiers show balanced accuracies of less than 65%; however, they perform better when using feature transformation based on MLO. The achievement of an accuracy of 90% using the K-Nearest Neighbor classifier with the suggested feature modification is quite noteworthy.

Iqbal et al. [10] examined a database of paddy leaf diseases, including Brown Spot and Bacterial Blight, utilizing images of healthy and infected leaf for classification. The system predicted and classified rice leaf diseases, aiding both farmers and exporters by estimating disease occurrences and vital production parameters. Prototype picture acquisition and machine vision models enabled real-time detection and categorization in rice cultivation. Notably, KNN achieved 67.18%, Inception V3 reached 93.57%, and VGG19 attained 97.94% accuracy. The study emphasized dataset quality and size in deep learning, highlighting the methodology's potential to enhance rice cultivation and exports.

A CNN-based DL architecture, incorporating transfer learning (TL) techniques, was proposed and implemented by Gautam et al. [11], focused on the significant impact of leaf diseases on paddy crop health. TL models such as VGG19, ResNet, VGG16, SqueezeNet, and InceptionV3 were utilized. The methodology involved preprocessing of leaf images followed by semantic segmentation to isolate regions of interest for fine-tuning TL models. The model specifically targeted biotic diseases affected by bacteria and fungi, achieving an impressive accuracy rate of 96.4%. The model demonstrated superior performance compared to existing approaches.

Advanced deep learning techniques were employed by Yakkundimath et al. [12] to classify rice plant disease symptoms using VGG-16 and GoogleNet CNN models through TL. After rigorous threefold cross-validation, GoogleNet and VGG-16 achieved average accuracies of 91.28% and 92.24%, respectively. The dataset used consisted of 12,000 labeled images representing 24 distinct symptoms across three types of rice diseases. Notably, VGG-16 showed slightly better performance compared to GoogleNet in disease classification. These results suggest promising applications for automating disease identification in rice plants, benefiting agricultural practices and policymaking.

Various machine learning and deep learning techniques were examined by Tejaswini et al. [13] to identify diseases affecting rice leaves, aiming to enhance crop yield for farmers. The study

evaluated the effectiveness of different approaches by analyzing metrics like accuracy, recall, and precision. It was found that deep learning models outperformed traditional machine learning methods in disease detection. Notably, a 5-layer convolutional network exhibited the highest accuracy at 78.2%, surpassing models like VGG16, which achieved an accuracy of 58.4%. Additionally, involved classifying rice leaf diseases using various deep learning methods, including VGG19, VGG16, Xception, ResNet, and a custom 5-layer convolutional network. Results indicated that the custom 5-layer convolutional network performed the best, achieving approximately 6% higher accuracy than standard deep learning models.

Haque et al. [14] addressed the issue of rice leaf diseases, which had been a significant concern for global rice cultivation. Recognizing farmers' limited ability to accurately diagnose these diseases, the research opted for YOLOv5, identified as a promising approach. An extensive dataset comprising 1500 annotated images was utilized for training the YOLOv5 model, covering a wide range of disease manifestations. The methodology involved training and evaluating the model to meet specific performance metrics, including recognition precision (90%), recall (67%), mean Average Precision (mAP) value (76%), and F1 score (81%). While the YOLOv5 model demonstrated promising results, certain limitations persisted, such as the need for further validation across diverse datasets and potential challenges in real-world deployment due to computational resource requirements.

Rani et al. [15] undertook a comprehensive exploration of methods for detecting rice leaf diseases. Among various approaches considered, the deep CNN with ResNet-50 was selected for its efficacy in identifying plant diseases. Given the global significance of rice cultivation, safeguarding crops became a priority, necessitating proactive measures against diseases and threats. Utilizing the deep CNN method facilitated the processing of extensive datasets, resulting in disease identification with an impressive accuracy of 97.3%.

In the pursuit of improving paddy disease detection and classification, Almasoud et al. [16] introduced an Efficient DL based Fusion Model (EDLFM-RPD). The methodology incorporated preprocessing steps like median filtering and K-means segmentation to identify affected areas, while feature extraction combined handcrafted Gray Level Co-occurrence Matrix (GLCM) and Inception-based deep features. Classification utilized Salp Swarm Optimization with Fuzzy SVM. A series of simulations were conducted to verify the efficacy of the EDLFM-RPD model, which yielded promising results, achieving a maximum accuracy of 96.170%.

Recognizing the paramount importance of timely disease detection and classification, the Bracino et al. [17] centered on utilizing DL algorithms, including EfficientNet-b0, Places365-GoogLeNet and MobileNet-v2, for this purpose. The targeted diseases encompassed bacterial leaf blight, hispa, bacterial panicle blight, bacterial leaf streaks, downy mildew, and rice tungro disease, reflecting the diverse range of threats to rice cultivation. Through extensive experimentation, it was discerned that EfficientNet-b0 is the most efficient model with accuracy of 97.74%.

Prathima and Nath [18] examined the classification efficacy of various CNN architectures in identifying rice plant diseases. Results revealed that AlexNet achieved the highest accuracy at 89.4%, closely followed by VGG-16, VGG-19, and ResNet-50, which exhibited comparable performance. MobileNet emerged as a viable option for mobile apps development due to its efficiency. The developed Generic Paddy Plant Disease Detector (GP2D2) aimed to equip novice farmers with digital disease detection capabilities akin to expert farmers. Conventional disease identification methods were deemed less effective over large agricultural areas, underscoring the importance of the mobile application. Drones equipped with cameras were proposed for capturing paddy images for disease identification via the app. The study offered valuable insights for selecting appropriate architectures for real-time disease identification applications in paddy plants. The mobile application framework's flexibility allowed for easy customization by updating or replacing the existing model as necessary.

A critical gap exists in the development of DL models that can effectively detect and classify paddy leaf diseases under real-world conditions, addressing challenges such as variability in background, color issues, and the presence of contaminated elements in images. Existing methods, including unsupervised approaches and traditional machine learning algorithms like SVM, KNN, and Back Propagation Neural Network, encounter limitations such as complexity, time consumption, and difficulty in handling noise and lighting problems. Moreover, these methods may struggle with diseases exhibiting similar morphology and color, limiting their applicability across diverse environmental conditions and stages of crop growth. Therefore, there is a pressing need for research focused on enhancing the robustness and scalability of DL models for paddy leaf disease detection and classification, considering aspects such as variable lighting conditions, weather fluctuations, and the presence of multiple disease types simultaneously. Additionally, research efforts should aim to bridge the gap between theoretical advancements and practical deployment in agricultural settings, particularly in resource-constrained environments where computational resources and technical expertise may be limited. Tackling these obstacles will help create better tools to monitor and control paddy leaf diseases, leading to higher crop yields and improved food security.

III. MATERIALS AND METHODS

Efficient detection and classification of paddy leaf diseases are imperative to optimize agricultural yield and ensure food security, emphasizing the urgency for the development of a robust and scalable deep learning model tailored for real-world applications. A detailed visualization of the proposed method is given in Fig. 1.

A. Dataset

The dataset containing paddy leaf diseases was acquired from Kaggle repository, [23] comprising a total of 2627 images distributed across the training and validation folders. It encompasses six distinct rice leaf diseases, namely Brown Spot, Bacterial Leaf Blight, Healthy, Leaf Scald, and Narrow Brown Spot, Leaf Blast. Some sample images of paddy leaf disease from the dataset are represented by Fig. 2.

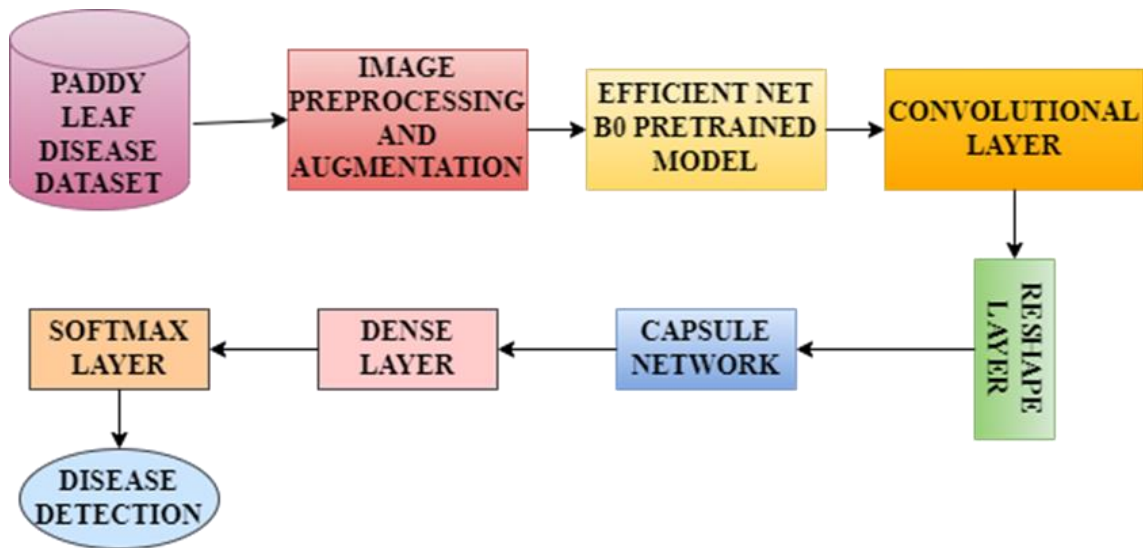


Fig. 1. Schematic illustration of the proposed model.



Fig. 2. Dataset sample images.

B. Image Preprocessing and Data Augmentation

Following the dataset collection phase, the images underwent a series of preprocessing and augmentation steps to prepare them for training. Preprocessing involves standardizing the images, ensuring consistent pixel values and dimensions. In this case, pixel values were rescaled to fall within the range of 0 to 1, to aid in model convergence during training. Augmentation methods were then applied to boost the variability of the dataset, enhancing the capability to generalize to unseen data. These techniques included shear transformations, zooming, flipping (both horizontally and vertically), and rotation (up to 30 degrees). These augmentations mimic real-world variations that might occur in the images, such as changes in perspective or orientation. Subsequently, the images were scaled down to a target size of 224x224 pixels, a standard input size. This resizing ensures uniformity in input dimensions across all images, facilitating model training. To optimize memory usage during

training, the images were batched into groups of 64. Additionally, the class labels associated with each image were encoded in categorical format. This encoding represents each class label as a binary vector, where each element corresponds to a specific class and indicates its presence or absence of the paddy leaf disease in the image.

C. Architecture of Proposed Model

The pre-processed images are input into the hybrid deep learning architecture proposed in this study. This model combines the EfficientNetB0 model with a Capsule network for enhanced performance in disease classification.

1) *EfficientNetB0*: EfficientNetB0 is a highly efficient CNN architecture. It balances model depth, width, and resolution through compound scaling, offering advanced performance across various computer vision tasks while

minimizing computational demands. EfficientNetB0 is renowned for its modular design, featuring a stem convolutional layer that serves as the initial processing stage for input images as Fig. 3.

Following the stem layer, the architecture comprises multiple sequences of MobileNetV2-like MBCConv blocks, which have squeeze-and-excitation mechanisms, shortcut connections, and depth wise separable convolutions [19]. These components collectively contribute to the model's efficiency by reducing computational complexity while preserving representational capacity. The number of MBCConv blocks in each sequence, as well as the scaling factors applied to network dimensions, are determined through a compound scaling method. This approach ensures a balanced adjustment of network width, depth, and resolution, thereby optimizing the model's performance across various computational constraints. The layers in the network are scaled by a factor α . If the original network has L layers, the scaled network has approximately $\alpha * L$ layers. The width of each layer (number of channels) is scaled by a factor β . If the original network has W channels in a layer, the scaled network has approximately $\beta * W$ channels. The input image resolution is scaled by a factor γ . If the original input resolution is $R \times R$ pixels, the scaled input resolution is approximately $\gamma * R \times \gamma * R$ pixels. The compound coefficient φ is defined as the geometric mean of $\alpha, \beta,$ and γ given by Eq. (1).

$$\varphi = \sqrt[3]{\alpha * \beta * \gamma} \quad (1)$$

One of the notable features of the EfficientNetB0 architecture is its utilization of global average pooling, which facilitates dimensionality reduction by summarizing spatial information across feature maps. This pooling operation aids in capturing essential features while mitigating the possibility of overfitting, thereby boosting the capacity of generalization. The architecture consists of nine stages, each with specific operators, resolutions, channels, and layers, designed to process input data at different levels of complexity and abstraction. EfficientNetB0 is typically pretrained on large-scale image datasets such as ImageNet, enabling it to learn generic features from diverse visual data [20]. This pretrained model can then be fine-tuned

on smaller, task-specific datasets to adapt its learned representations to the nuances of the target domain, making it highly versatile for various image classification tasks.

2) *Capsule network*: Drawing inspiration from the hierarchical organization of biological neural structures, Capsule Neural Networks, or CapsNets, represent a type of artificial neural network (ANN) designed to mimic these hierarchical relationships. Unlike conventional neural networks, CapsNets introduce capsules, termed as digit capsules, as fundamental units to better handle hierarchical structures and variations in data [21]. These capsules encapsulate activation information and spatial relationships, outputting pose parameters alongside activations to represent specific entities or object parts. CapsNets employ dynamic routing to refine coupling coefficients based on pose parameter agreement, enhancing recognition of intricate data patterns and capturing complex spatial hierarchies. The CapsNet architecture includes an encoder network, consisting of layers like Convolutional, PrimaryCaps, and DigitCaps, to convert image inputs into vectors containing essential parameterization parameters as shown in Fig. 4.

The PrimaryCaps layer clusters neurons into capsules to capture important patterns, while the DigitCaps layer represents specific entity types and encodes their instantiation parameters. Capsule networks utilize dynamic routing to update coupling coefficients between lower-level and higher-level capsules, aiming to increase agreement between predictions and input vectors [22]. Additionally, CapsNets feature a DecoderNetwork as illustrated in Fig. 5, responsible for reconstructing input images from the data stored in DigitCapsules, facilitating faithful image reconstruction using instantiation properties. This reconstruction process contributes to both classification accuracy and meaningful image reconstruction, aligning with the training objective of Capsule Networks. It calculates the loss for each training example and output class using Eq. (2).

$$L_n = T_n \max(0, m^+ - \|v_n\|)^2 + \lambda(1 - T_n) \max(0, \|v_n\| - m^-)^2 \quad (2)$$

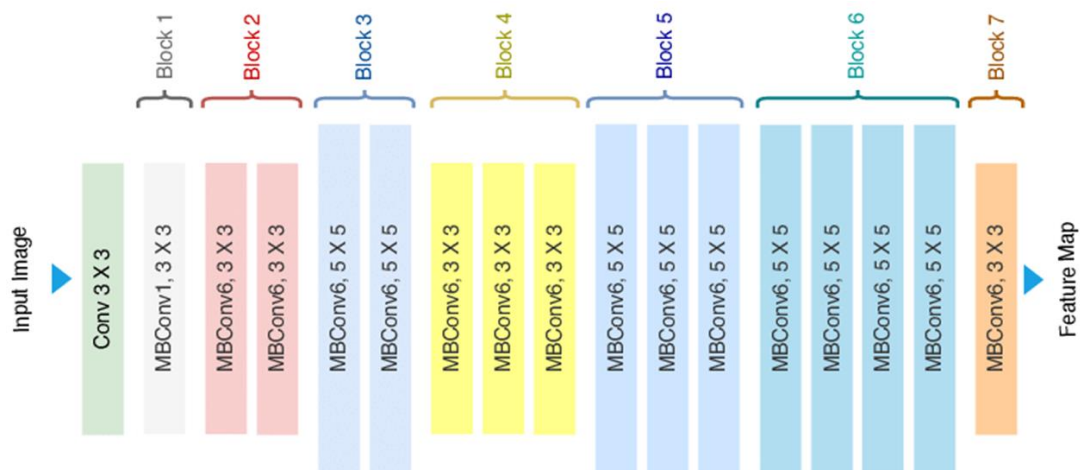


Fig. 3. Fundamental architecture of EfficientNetB0.

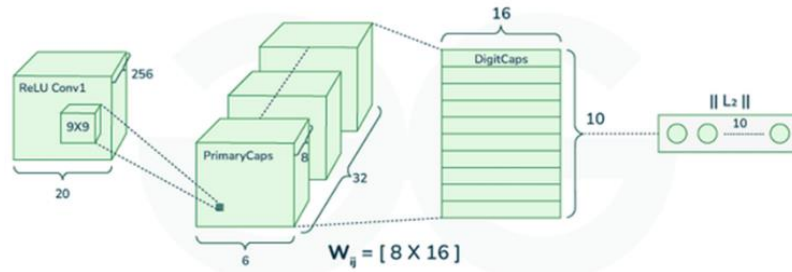


Fig. 4. Encoder network of CapsNet.

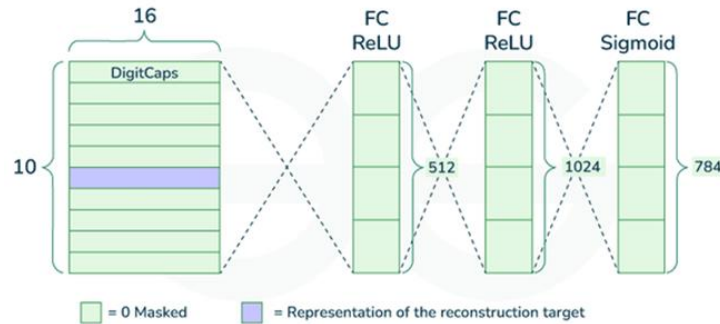


Fig. 5. Decoder network of CapsNet.

where L_n denotes the margin loss for the n -th digit capsule. The binary indicator T_n represents the activity vector for the n -th digit capsule as v_n , with its length indicated as $\|v_n\|$. The positive and negative margins are represented as m^+ and m^- respectively. Additionally, λ signifies the down-weighting factor for the loss from inaccurate digit capsules. Dynamic routing in capsule networks updates coupling coefficients between lower-level and higher-level capsules to enhance agreement. This iterative update process is governed by Eq. (3),

$$c_{ij} = \frac{\exp(b_{ij})}{\sum_k \exp(b_{ik})} \quad (3)$$

where b_{ij} denotes the log prior probabilities of the coupling coefficients

3) *Proposed hybrid model:* The proposed hybrid deep learning model combines the strengths of EfficientNetB0 and Capsule Network to effectively detect and classify diseases in paddy plants. EfficientNetB0 serves as the backbone of the model, leveraging its pretrained weights from ImageNet to capture intricate hierarchical features from input images. This pretrained model is adept at extracting meaningful patterns, edges, and textures from images, providing depiction of the input data. To further process the features extracted by EfficientNetB0, a Global Average Pooling layer is induced.

This layer preserves crucial information while minimizing the feature maps' spatial size, facilitating computational efficiency and preventing overfitting. Following the Global Average Pooling layer, Dense layers are introduced for additional feature extraction and combination. ReLU activation functions, which are fitted to every Dense layer, add non-linearity to the model and improve its ability to represent intricate correlations found in the data. After the Dense layers,

the output is reshaped to prepare the data for integration with the Capsule Network. This reshaping step ensures that the features extracted by the preceding layers are appropriately formatted and compatible with the initial requirements of the Capsule Network.

The Capsule layer receives the reshaped output from the Dense layers and performs a series of operations to learn hierarchical features. This includes applying a 2D convolution to the input, reshaping the resulting feature maps, and applying a squashing activation function to encapsulate the activation information and spatial relationships within the data. By doing so, the Capsule layer can effectively encode complex patterns and variations present in the input images. Finally, a dense layer with softmax activation function is employed at the output layer for disease detection. This layer computes the probability distribution over the different disease classes, allowing the model to classify input images into the corresponding category of disease with high accuracy. Thus, the hybrid deep learning model seamlessly integrates the strengths of EfficientNetB0 and Capsule Network, enabling robust and efficient detection and classification of diseases in paddy plants.

4) *Hardware and software setup:* The model utilized for this study includes an Intel Core i7-6850K 3.60 GHz 12-core processor and a NVIDIA GeForce GTX 1080 Ti GPU with 2760 4MB memory. Google Collaboratory served as the workstation platform. The implementation of the proposed work was done using Python, a widely-used programming language recognized for its readability and ease of use. Python's extensive library ecosystem and dynamic typing, coupled with strong community support, have led to its broad acceptance across diverse industries and fields. Table I outlines the specifications of the hyperparameters utilized in the study.

TABLE I. SPECIFICATIONS OF HYPERPARAMETERS

Hyperparameter	Values
Routings	3
Loss Function	Categorical Cross entropy
No. of epochs	30
Optimizer	Adam
Batch Size	64
Activation Function	ReLu, Softmax

IV. RESULT AND DISCUSSION

A. Performance Evaluation

The assessment metrics given in Table II are utilized to determine the effectiveness of the suggested hybrid architecture.

TABLE II. EVALUATION METRICS

Performance Metrics	Equations
Accuracy	$(TP + TN) / (TP + TN + FP + FN)$
Precision	$TP / (TP + FP)$
Recall	$TP / (TP + FN)$
F1 Score	$2 * (Precision * recall) / (Precision + recall)$

where, *TP*-true positives, *TN*-true negatives, *FP*-false positives and *FN*-false negatives

Table III represents the performance evaluation of the proposed model for the detection of paddy leaf disease with respect to accuracy, recall, precision, and f1 score.

TABLE III. EVALUATION REPORT OF PROPOSED METHOD

Performance Metrics	Results Obtained
Accuracy	97.86%
Precision	97.98%
Recall	98.01%
F1- Score	97.99%

The provided analysis examines the effectiveness of the model using various metrics. The accuracy score, at 97.86%, indicates the percentage of instances that were correctly identified out of all. Precision, measuring the accuracy of positive predictions, is exceptionally high at 97.98%, suggesting

that the model has a high probability of being accurate when it predicts a favorable result. Similarly, the recall value, indicating the ability to capture true positive cases, is also impressive at 98.01%, implying that the model effectively identifies a significant portion of the actual positive cases. This high precision and recall values collectively represent that the model achieves good equilibrium between minimizing false positives (incorrectly identified positives) and false negatives (missed positives). The F1-Score, a combined measure of precision and recall, further validates the model's performance, yielding a high score of 97.99%. This metric confirms the model's ability to maintain a harmonious trade-off between precision and recall, emphasizing its robustness in classification tasks. Table IV illustrates the classification report of the suggested model which effectively detect the paddy leaf disease.

TABLE IV. CLASSIFICATION REPORT OF SUGGESTED METHOD

Paddy Leaf Disease	Precision	F1-Score	Recall
Leaf Scald	0.97	0.98	0.98
Leaf Blast	0.96	0.98	0.97
Narrow Brown Spot	0.98	0.97	0.97
Brown Spot	0.97	0.98	0.97
Bacterial Leaf Blight	0.97	0.97	0.97
Healthy	0.98	0.97	0.98

Accuracy and loss plots are essential visualizations for evaluating model performance during training. The accuracy plot depicts how the model's predictive accuracy changes over training epochs, while the loss plot shows variations in the model's loss function. These plots offer insights into aspects like model convergence, overfitting, or underfitting, helping to refine the model for better performance. Fig. 6 presents these plots, indicating trends in accuracy and loss across epochs. Fig. 7 presents the confusion matrix, to evaluate the classification model's accuracy. It displays true positives, false negatives, true negatives, and false positives, providing a comprehensive view of classification outcomes. Each cell in the matrix represents a combination of true and predicted labels, highlighting the model's classification performance. The main diagonal represents correct classifications, while off-diagonal elements indicate misclassifications.

The detection output of the suggested hybrid model that effectively detect the paddy leaf disease is shown by Fig. 8.

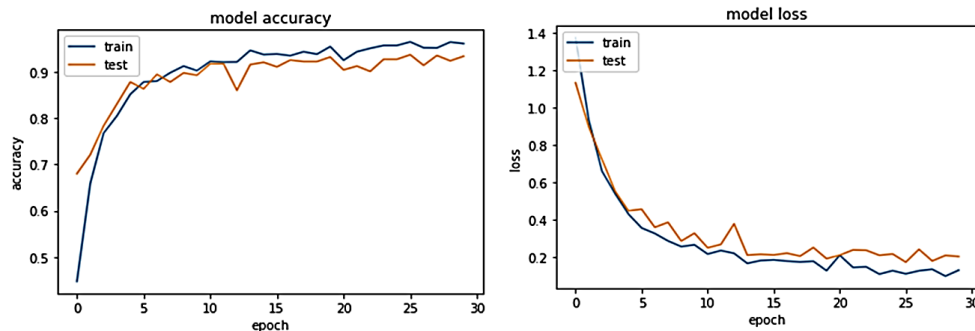


Fig. 6. Accuracy and loss plot of the hybrid model.

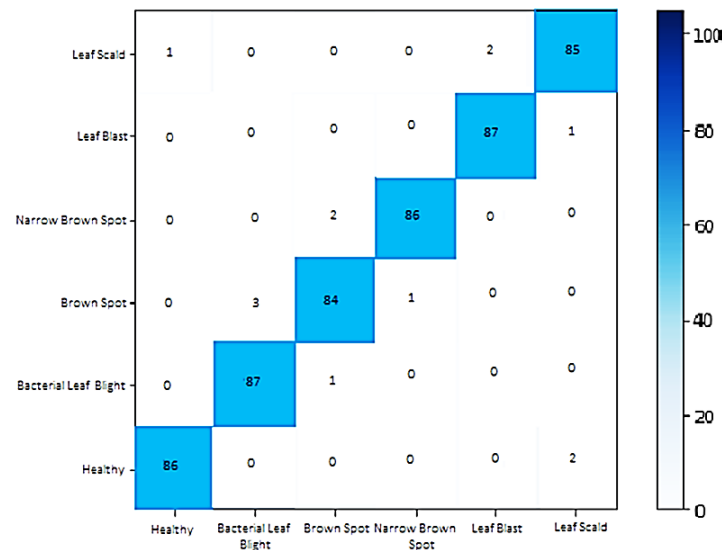


Fig. 7. Confusion matrix of the hybrid method.

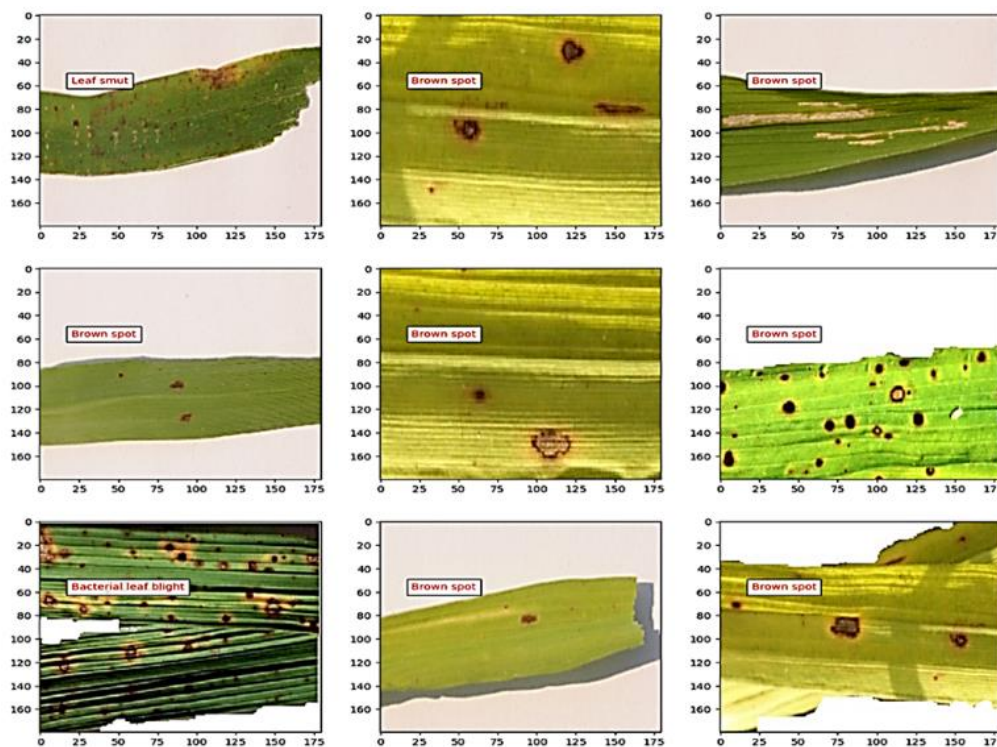


Fig. 8. Detection output.

B. Performance Comparison

Table V compares the performance of the proposed hybrid network with conventional methods based on ML and DL, providing a comprehensive analysis of their effectiveness. The analysis of various deep learning methodologies highlights the superior performance of the proposed hybrid model. While Convolutional Neural Networks (CNNs) such as VGG-16 and advanced hybrid CNN models demonstrated high accuracy, reaching up to 97%, and other models like YOLOv8 and

Double-branch DCNN with CBAM also performed well with accuracies of 97.73% and solid precision and recall metrics, the proposed model stands out. By integrating EfficientNetB0 with a Capsule Network, it achieved the highest accuracy of 97.86%, surpassing other approaches. It also excelled in precision, recall, and F1-score, demonstrating its robust capability in delivering superior overall performance compared to existing methods. This suggests that the hybrid model not only achieves better accuracy but also provides enhanced reliability and effectiveness in its predictions.

TABLE V. CLASSIFICATION REPORT OF PROPOSED METHOD

Author	Methodology Used	Results
Kulkarni and Shastri [5]	CNN based on VGG-16 model, preprocessing with Kaggle dataset	Accuracy: 95%
Jesie et al. [6]	Hybrid CNN model outperforming DNN, DBN, LSTM, and RNN	Accuracy: 97%, F-measure: 92.3%, Precision: 93.1%, Recall: 92.1%, Sensitivity: 93.4%, Specificity: 94.27%
Trinh et al. [7]	YOLOv8 model with data augmentation techniques	Precision: 89.6, Recall: 83.5, F1-score: 86.4, mAP: 88.9
Bi and Wang [9]	Double-branch DCNN (DBDCNN) model integrated with CBAM	Accuracy: 97.73%
Bharanidharan et al. [10]	Modified Lemurs Optimization Algorithm with machine learning methods	Balanced accuracy: 90%
Iqbal et al. [11]	Utilized KNN, Inception V3, and VGG19 with varying accuracies	KNN: 67.18%, Inception V3: 93.57%, VGG19: 97.94%
Gautam et al. [12]	TL models such as InceptionV3, VGG16, ResNet, SqueezeNet, and VGG19 with preprocessing and segmentation	Accuracy: 96.4%
Yakkundimath et al. [13]	Transfer learning using VGG-16 and GoogleNet CNN models	VGG-16: 92.24%, GoogleNet: 91.28%
Tejaswini et al. [14]	Various deep learning models including VGG19, VGG16, Xception, ResNet, and custom 5-layer CNN	Custom CNN: 6% higher accuracy than standard deep learning models
Haque et al. [15]	Utilized YOLOv5 model with specific performance metrics	Recognition precision: 90%, Recall: 67%, mAP: 76%, F1 score: 81%
Rani et al. [16]	Deep CNN with ResNet-50	Accuracy: 97.3%
Almasoud et al. [17]	Efficient Deep Learning based Fusion Model (EDLFM-RPD) with preprocessing and feature extraction	Maximum accuracy: 96.170%
Bracino et al. [18]	DL algorithms including MobileNet-v2, EfficientNet-b0, and Places365-GoogLeNet	Average accuracy: 97.74%
Proposed Model	Hybrid Deep learning model combining EfficientNetB0 and Capsule Network	Accuracy of 97.86%, Precision of 97.98%, Recall of 98.01%, and F1-Score of 97.99%.

V. CONCLUSION

The detection and classification of paddy leaf diseases are critical aspects of modern agricultural practices, contributing significantly to crop management, yield optimization, and food security. This study presents a comprehensive exploration of the suggested hybrid DL model for the effective identification of paddy leaf diseases, addressing the limitations of existing methodologies. Using a combination of the EfficientNetB0 architecture and Capsule Network, the proposed model demonstrates remarkable performance in terms of accuracy, precision, recall, and F1-Score, as evidenced by the evaluation metrics. With an accuracy of 97.86% and precision, recall, and F1-Score values all exceeding 97%, the model demonstrates its capability to precisely detect and classify paddy leaf diseases, including Brown Spot, Leaf Scald, Narrow Brown Spot, Leaf Blast, Bacterial Leaf Blight, and Healthy leaves. Moreover, the hybrid reliability is further underscored by its comparison with conventional approaches, where it consistently outperforms existing methods in terms of accuracy and efficacy. The suggested hybrid DL model represents advancement in the field of agricultural technology, offering an efficient solution for identification and classification of paddy leaf diseases. This model holds immense potential to revolutionize crop management practices, contribute to global food security efforts, and empower farmers with actionable insights for sustainable agriculture. Future work will involve expanding the model to detect a broader range of paddy leaf diseases and integrating it with real-time processing for on-field use. Efforts will also focus on combining the model with environmental data to enhance diagnostic accuracy. Additionally, validating the model through

practical field trials will be essential for ensuring its effectiveness in real-world agricultural settings.

ACKNOWLEDGMENT

I would like to express my sincere gratitude to all those who contributed to the completion of this research paper. I extend my heartfelt thanks to my supervisor, my family, my colleagues and fellow researchers for their encouragement and understanding during the demanding phases of this work.

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