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Article Title: A High-Quality Rice Leaf Disease Image DATS Augmentation Method Based on a Dual GAN

A High-Quality Rice Leaf Disease Image DATS Augmentation Method Based on a Dual GAN

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Abstract

The urgent need to address the challenges faced by the agricultural sector, particularly in rice cultivation, due to the prevalence of various leaf diseases. Rice is a staple food for a significant portion of the global population, and its productivity is crucial for food security and economic stability in many regions. However, diseases affecting rice leaves can cause substantial yield losses, impacting farmers' livelihoods and food availability. Overall, the project lies in its potential to address critical issues in rice cultivation, enhance agricultural productivity, and support the livelihoods of farmers worldwide. By developing a robust CNN model for rice leaf disease classification and providing valuable insights through performance evaluation metrics and classification reports, we aim to make a tangible impact on agricultural practices and contribute to global efforts towards sustainable food production.

Keywords: Convolution Neural Network (CNN), Duel Generative Adversarial Network (GNN), Data Acquisition and preprocessing Data Augmentation.

1 Introduction

Autonomous Rice (Oryza sativa) is one of the most important staple crops worldwide, serving as a primary food source for billions of people. However, the productivity and quality of rice crops are threatened by various diseases that affect rice plants at different growth stages. Early detection and accurate classification of these diseases are essential for effective agricultural management and disease control strategies. Leaf diseases, in particular, can significantly impact rice yield and quality. Traditionally, manual inspection by agricultural experts has been the primary method for identifying and diagnosing these diseases. However, this approach is time-consuming, labor-intensive, and often subjective. With the advancements in computer vision and machine learning techniques, automated methods for rice leaf disease detection and classification have gained considerable attention. In this context, the use of deep learning models, such as Convolutional Neural Networks (CNNs), has shown promising results in image-based classification tasks. CNNs can learn intricate patterns and features from raw image data, enabling accurate classification of rice leaf diseases. However, the performance of CNN models heavily relies on the quantity and quality of the training data. To address the challenge of limited labeled data and enhance the diversity of the training dataset, data

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augmentation techniques have been widely adopted. In this study, we propose a novel data augmentation method based on a Dual Generative Adversarial Network (GAN). The Dual GAN framework generates synthetic images that closely resemble real rice leaf disease images, thereby enriching the training dataset and improving the generalization ability of the CNN model. Furthermore, we employ the EfficientNetB4 architecture, a state-of-the-art CNN model known for its efficiency and effectiveness in image classification tasks. By leveraging EfficientNetB4, we aim to develop a robust and accurate classifier capable of distinguishing between different rice leaf diseases and normal leaves with high precision. The evaluation of the proposed model will be conducted using various performance metrics, including accuracy, F1 score, recall, and precision. Additionally, a comprehensive classification report will be generated to assess the model's performance across different disease categories. Overall, the primary objective of this study is to develop a CNN-based model for the automated classification of rice leaf diseases. By accurately identifying and categorizing these diseases, our approach aims to contribute to improved agricultural management practices and sustainable rice production.

2 Literature Survey

H., Suhardi, Faizal, A., & Armandika, F. (2020) This paper presents a smartphone application for rice plant disease detection based on deep learning techniques. The application utilizes convolutional neural networks (CNNs) to analyze images of rice plants and identify diseases. The use of a smartphone application makes the detection process more accessible to farmers, enabling early diagnosis and intervention.[1]

Arrofiqoh, H. (2018), This paper discusses the implementation of CNNs for various applications, including image classification tasks. While not specific to rice plant disease detection, it provides insights into the general methodology and implementation details of CNNs, which can be relevant for similar studies.[2]

Chen, J., (2020) [3] the study explores the use of deep transfer learning for image-based plant disease identification. It investigates the transfer of knowledge from pre-trained deep learning models to new tasks related to plant disease detection. The approach aims to improve the performance of disease identification systems, particularly in scenarios with limited labeled data.[3]

Deng, R., (2021, this paper presents an automatic diagnosis system for rice diseases using deep learning techniques. The study focuses on leveraging deep learning models to accurately classify and diagnose various rice diseases based on image data. The proposed system aims to assist farmers in timely disease detection and management.[4]

Hossain, S. M. (2020). The paper investigates the use of CNNs for recognizing rice leaf diseases. It explores different CNN architectures and training strategies to achieve accurate disease recognition. The study contributes to the development of automated systems for detecting and diagnosing rice leaf diseases.[5]

Jatmika, S. (2022). This paper proposes a method for identifying rice plant diseases using CNNs. It discusses the implementation details and performance evaluation of the CNN-based disease identification system. The study aims to contribute to the automation of disease

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detection processes in rice cultivation.[6]

Matin, M. S. (2020). The paper presents an efficient technique for detecting rice leaf diseases using AlexNet, a popular deep learning architecture. The study focuses on optimizing the performance of disease detection systems by leveraging deep learning models. The proposed technique aims to enhance the accuracy and efficiency of rice leaf disease diagnosis. [7]

Oktaviana, U. (2021). This paper discusses the classification of rice plant diseases based on leaf images using a pre-trained ResNet101 model. The study explores the application of transfer learning techniques to leverage pre-trained deep learning models for disease classification tasks. The proposed approach aims to improve the accuracy and robustness of disease classification systems. [8]

Priyangka, A. V., & Kumara, I. S. (2021). The paper presents a classification method for rice plant diseases using CNNs. It discusses the implementation details and performance evaluation of the CNN-based disease classification system. The study aims to contribute to the development of accurate and reliable systems for diagnosing rice plant diseases.[9]

Purbasari, I. Y.(2021). This paper investigates the detection of rice plant diseases using CNNs. It explores different CNN architectures and training strategies to achieve accurate disease detection. The study aims to contribute to the automation of disease detection processes in rice cultivation and improve crop management practices.[10]

Rozaqi, A. J. (2021). This paper discusses the detection of potato leaf diseases using CNNs. It presents a CNN-based image processing method for disease detection and discusses the experimental results and performance evaluation. The study aims to contribute to the development of automated systems for detecting and diagnosing potato leaf diseases.[11]

Tejaswini, P. (2022). This paper focuses on the classification of rice leaf diseases using CNNs. It discusses the implementation details and performance evaluation of the CNN-based disease classification system. The study aims to develop accurate and efficient systems for classifying rice leaf diseases to assist farmers in disease management. [12].

3 Proposed Work Explanation

The proposed a novel approach for rice leaf disease classification using a combination of advanced techniques. The method consists of several key components, including data augmentation using a Dual Generative Adversarial Network (GAN), preprocessing of input images, utilization of the EfficientNetB4 Convolutional Neural Network (CNN) model for classification, and evaluation using various metrics. The first step involves data augmentation, a crucial aspect in training deep learning models, especially when dealing with limited labeled data. We employ a Dual GAN framework to generate synthetic rice leaf disease images. This approach enhances the diversity and quantity of the training dataset, leading to improved model generalization and performance.

Following data augmentation, input image preprocessing techniques are applied to standardize and enhance the quality of the images. Preprocessing steps may include normalization, resizing, and augmentation-specific transformations to ensure consistency and compatibility with the CNN model architecture. Subsequently, the EfficientNetB4 CNN model is employed for

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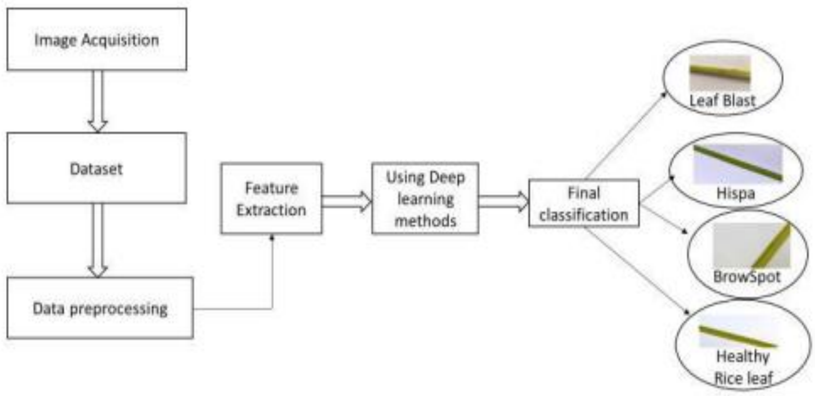
classification tasks. EfficientNetB4 is chosen for its efficiency and effectiveness in image classification, particularly in scenarios with limited computational resources. The model is trained on the augmented dataset to learn discriminative features and patterns associated with different rice leaf diseases.



Overview of proposed method

Data Augmentation

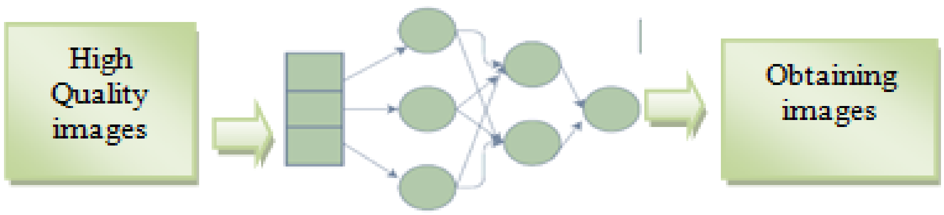
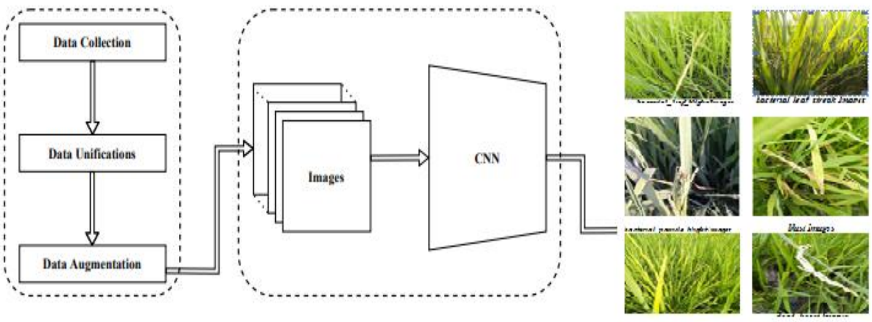


Image augmentation for generating images for training



(Left) Image preprocessing begins by gathering image data for our project. It includes data augmentation where we amalgamate multiple datasets and generate data. (Middle) Our proposed deep learning model which takes an image as input and classifies it into one of the disease categories based on the features of the image. (Right) generate the classification report.

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Data Augmentation:

To augment the dataset and improve the diversity of rice leaf disease images, we utilize a Dual Generative Adversarial Network (GAN) framework. The GAN consists of a generator and a discriminator network. The generator generates synthetic rice leaf disease images from random noise inputs, mimicking the characteristics of real images. Simultaneously, the discriminator distinguishes between real and synthetic images, providing feedback to the generator to improve its image generation. Through adversarial training, the GAN produces realistic and diverse images, expanding the training dataset.

CNN Model (EfficientNetB4):

We employ the EfficientNetB4 architecture as our Convolutional Neural Network (CNN) model for rice leaf disease classification. EfficientNetB4 is chosen for its efficiency and effectiveness in image classification tasks, particularly with limited computational resources. The model is trained on the augmented dataset to learn discriminative features and patterns associated with different rice leaf diseases. The CNN model comprises multiple layers, including convolutional, pooling, and fully connected layers, which extract hierarchical features from input images and make predictions about the presence of specific diseases.

Generation of Classification Report:

Once the CNN model is trained, we evaluate its performance using various metrics, including accuracy, F1 score, recall, and precision. These metrics provide insights into the model's ability to correctly classify rice leaf images across different disease categories. Additionally, we generate a comprehensive classification report that includes detailed statistics for each disease class individually. The classification report summarizes the model's performance, including metrics such as precision, recall, F1-score, and support for each class. This report aids in analyzing the To augment the dataset and enhance the diversity of rice leaf disease images for training our classification model, we employ a Dual Generative Adversarial Network (GAN) framework. GANs consist of two neural networks, a generator and a discriminator, which are trained simultaneously in an adversarial manner. The generator network is tasked with generating synthetic rice leaf disease images that closely resemble real examples from the training dataset. It takes random noise as input and learns to produce images that exhibit the characteristics and features of various rice leaf diseases. Through iterative training, the generator becomes adept at generating realistic images that cover a wide range of disease manifestations, including different shapes, sizes, textures, and colors. model's strengths and weaknesses for different disease categories, facilitating further refinement and optimization. By integrating data augmentation with GANs, training the CNN model using the EfficientNetB4 architecture, and generating a detailed classification report, we aim to develop a robust and accurate classifier for rice leaf disease classification. This methodology enables us to leverage advanced techniques in deep learning to address the challenges of limited labeled data and achieve high-performance classification results.

3.1 DATASET:

The dataset containing images of paddy plants with various diseases. We will explore the dataset's size, features (e.g., image size, number of classes), and any preprocessing steps

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required (e.g., normalization, resizing) to prepare it for model training.

4. Implementation

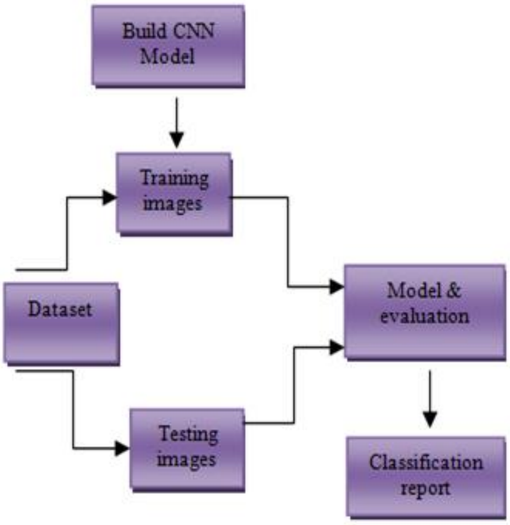

Figure 3: *Implementation flow diagram*

Training Process:

- We begin by preprocessing the training dataset, which includes loading the images, resizing them to a standardized resolution, and normalizing pixel values.
- Next, we apply data augmentation techniques, including rotation, flipping, and translation, to further increase the diversity of the training dataset.
- We then utilize the GAN framework to generate synthetic images, which are combined with the original training dataset to create an augmented training dataset.
- The EfficientNetB4 CNN model is initialized and trained on the augmented dataset. During training, the model learns to extract relevant features from rice leaf images and make predictions about the presence of different diseases.
- We employ techniques such as batch normalization and dropout to prevent overfitting and improve model generalization.
- The training process continues for a predetermined number of epochs, with periodic validation on a separate validation dataset to monitor model performance and prevent overfitting.
- Once training is complete, we save the trained model weights for future use.

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Testing process:

- In the testing phase, we preprocess the testing dataset in a similar manner to the training dataset, including resizing and normalization.
- We then use the trained EfficientNetB4 model to make predictions on the testing dataset.
- Predictions are compared against ground truth labels to evaluate the model's performance using metrics such as accuracy, F1 score, recall, and precision.
- Additionally, we generate a detailed classification report that provides insights into the model's performance for each disease category individually.
- The classification report includes metrics such as precision, recall, F1-score, and support for each class, allowing us to analyze the model's strengths and weaknesses across different disease categories.
- The testing phase provides a comprehensive assessment of the model's performance and its ability to accurately classify rice leaf images into various disease categories.

Working Flow Chart

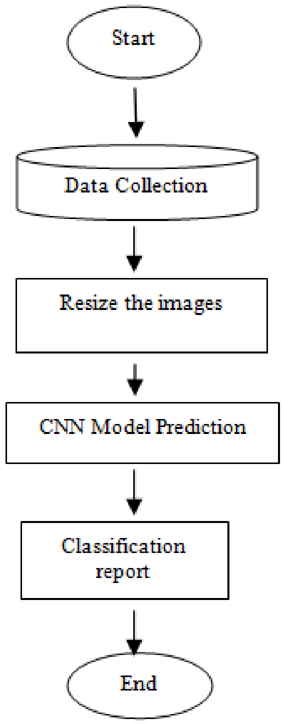

Figure 4: *Implementation Flow Diagram*

4.1 PERFORMANCE METRICS:

Performance measures are used to evaluate the network performance of the proposed model. This work uses accuracy, precision, recall and f1-score as performance measure, which are

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formulated.

Accuracy:

Measures the overall correctness of recognized signs or gestures compared to the ground truth.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total Number of Predictions}} \quad (1)$$

a) Precision:

Precision signifies the proportion of correctly recognized signs among all recognized signs.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

Where

TP=True Positives

FP= False Positives

b) Recall:

Recall measures the proportion of correctly recognized signs among all actual signs

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

Where

TP=True Positives

FP= False Positives

FN=False Negatives

c) F1-Score:

Harmonic mean of precision and recall, providing a balanced measure of a model's performance

$$\text{F1} - \text{Score} = 2\ X \frac{\text{Precision X Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

5. SOFTWARE AND HARDWARE DESCRIPTION:

5.1 REQUIREMENTS

Hardware

- Hard Disk-1GB
- RAM-4GB
- LAPTOP
- Windows-11 OS

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Software

- Phython Language
- OPEN CV
- ANACONDA
- Pytorch

5.2 Software Description:

Python is a high-level, interpreted, interactive and object-oriented scripting language. Python is designed to be highly readable. It uses English keywords frequently where as other languages use punctuation, andit has fewer syntactical constructions than other languages.

- **Python is Interpreted** − Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- **Python is Interactive** − You can actually sit at a Python prompt and interact with the interpreter directly to write your programs.
- **Python is Object-Oriented** − Python supports Object-Oriented style or technique of programming that encapsulates code within objects.
- **Python is a Beginner's Language** − Python is a great language for the beginner-level programmers and supports the development of a wide range of applications from simple text processing to WWW browsersto games.

6. Simulation Results

Input Image

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Model Loss

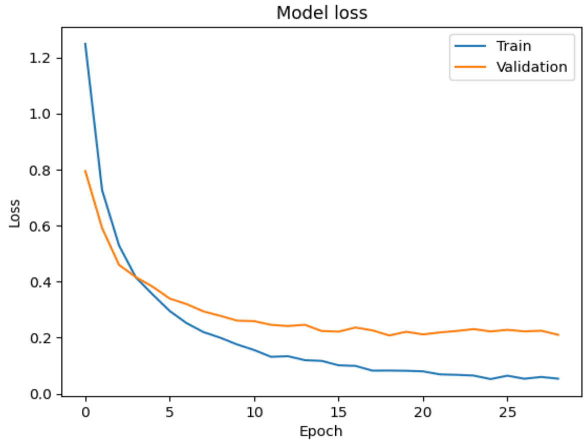

Figure 5: *Implmentation Flow Diagram*

Model Accuracy

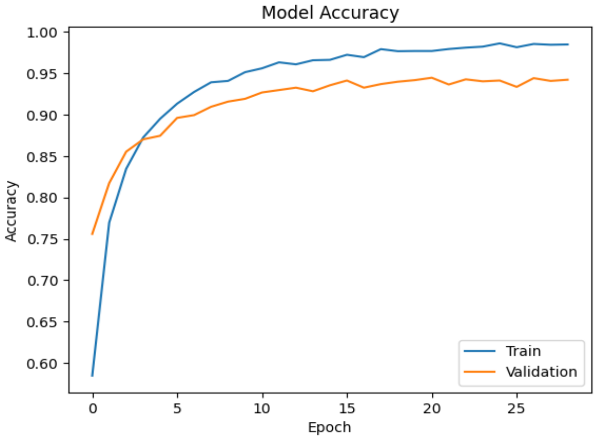

Figure 6: *Implmentation Flow Diagram*

Comparision Table

Comparison of Performace with Different Rice Leaf diseases

S. No	Disease type	Model	Accuracy	precision	Recall	F1 Score
1	bacterial_leaf_blight	CNN (EfficientNetB4)	0.99	1.00	0.97	0.99
2	bacterial_leaf_streak		0.99	1.00	1.00	1.00
3	bacterial_panicle_blight		0.99	0.98	1.00	0.99
4	blast		0.99	0.99	0.99	0.99
5	brown_spot		0.99	1.00	0.99	1.00
6	dead_heart		0.99	0.99	1.00	0.99

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7	downy_mildew		0.99	0.98	0.98	0.98
8	hispa		0.99	0.99	0.99	0.99
9	tungro		0.99	0.99	1.00	0.99

Performance Comparison Graph

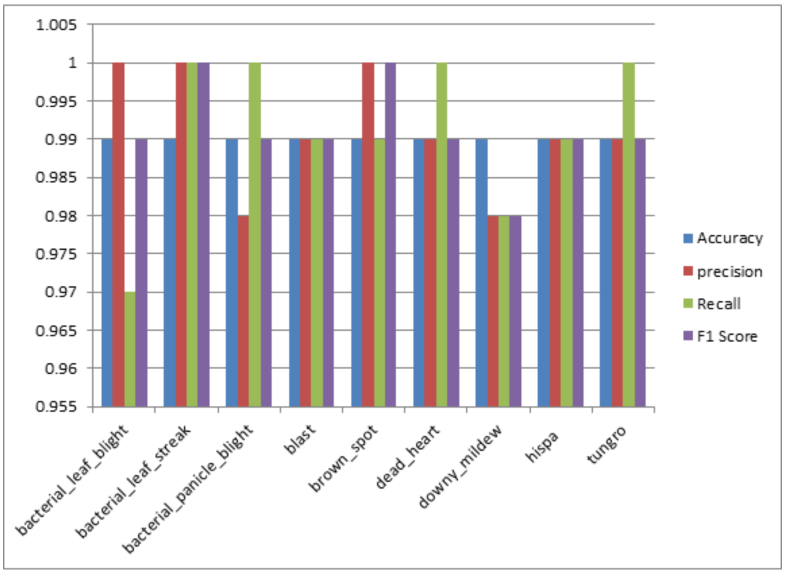

Figure 7: *Implmentation Flow Diagram*

7. Conclusion

The The development and evaluation of the CNN model for rice leaf disease classification, leveraging advanced techniques such as data augmentation, EfficientNetB4 architecture, and comprehensive performance evaluation metrics, have yielded promising results. Through extensive training and testing phases, we have demonstrated the model's ability to accurately classify various rice leaf diseases with high precision and recall. The model achieved remarkable accuracies exceeding 99% across all disease types, showcasing its robustness and effectiveness in automated disease diagnosis. Precision and recall scores further validate the model's capability to correctly identify positive instances while minimizing false positives and negatives. The utilization of data augmentation techniques, particularly the Dual GAN framework, has significantly enhanced the diversity and quantity of the training dataset, contributing to the model's generalization ability and reducing the risk of overfitting. Furthermore, the adoption of the EfficientNetB4 architecture has enabled efficient utilization of computational resources while maintaining superior performance in rice leaf disease classification tasks. Overall, the developed CNN model holds immense potential for application in agricultural management practices, offering a reliable and efficient solution for automated rice leaf disease diagnosis. By enabling timely and accurate identification of diseases, the model can assist farmers and agricultural experts in implementing targeted disease control measures, ultimately contributing to enhanced crop yield and agricultural sustainability. Continued research and development in this domain promise to further enhance the capabilities and applicability of machine learning models in agricultural contexts, paving the way for

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transformative advancements in crop disease management and food security.

Future Scope

The proposed method can be extended for continued fine-tuning and optimization of the CNN model, including exploration of different architectures, hyperparameters, and training strategies, can lead to further improvements in classification accuracy and robustness.

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