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Rice Plant Disease Detection Using Efficient Net V2

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Abstract
Rice is a staple crop feeding billions worldwide, yet its production is severely impacted by plant diseases, leading to significant economic losses and food insecurity. This project proposes an advanced Rice Plant Disease Detection System leveraging EfficientNetV2, a state-of the-art deep learning architecture, to achieve high accuracy in identifying and classifying rice diseases. The system incorporates geo-specific tagging during image acquisition, enabling location-based disease mapping and tailored crop recommendations. Key features include real-time disease detection, severity analysis, and actionable insights through a user-friendly dashboard with multilingual support. By addressing the limitations of traditional methods and existing automated solutions—such as overfitting, lack of scalability, and real-world adaptability—this project aims to provide an accurate, scalable, and accessible solution for farmers, ultimately promoting sustainable agriculture and enhancing rice crop yield.

Keywords: *Agriculture, Crop Yield, EfficientNetV2, Geo-Specific Tagging, Rice Plant Diseases.*

1. Introduction
Rice is a fundamental staple crop that feeds more than half of the global population, providing essential nutrition and calories. With rice cultivated in over 61% of the world's countries, its production is vital for food security, particularly in Asia, where it is the primary source of sustenance for millions of people [1]. As the global population continues to grow, the demand for rice is escalating, thereby placing immense pressure on agricultural systems to meet this rising need [1]. However, rice production faces significant challenges, especially from plant diseases that threaten the yield and quality of crops. Among the most damaging are rice leaf diseases, which can rapidly spread and cause extensive losses if not detected and managed in a timely manner. Traditional methods for detecting these diseases typically involve manual inspection of the crops, a process that is both labor-intensive and prone to errors [2]. Moreover, these methods often fail to provide timely or consistent results, especially when diseases are in their early stages. With the increasing scale of rice cultivation, such traditional techniques are no longer sufficient to ensure the sustainability of rice Production. As a result, there is an urgent need for more efficient and accurate systems that can automate the process of disease detection and aid in decision-making for disease management [3]. In recent years, the integration of machine learning (ML) and deep learning (DL) technologies has shown significant promise in revolutionizing plant disease detection. These advanced technologies enable automated systems to identify and classify diseases in rice plants with greater accuracy and speed compared to traditional methods [4]. Deep learning models, especially Convolutional Neural Networks (CNNs), have been widely employed for plant disease classification due to their ability to automatically learn features from raw images without the need for manual feature extraction [4]. CNNs, however, face challenges with large datasets and model complexity, often requiring substantial computational resources. Consequently, optimizing these models for real-time detection, accuracy, and scalability is essential [5]. The proposed rice plant disease detection system leverages EfficientNetV2, a lightweight yet highly efficient deep learning model, to address these

challenges. EfficientNetV2 provides a balanced trade-off between accuracy and computational efficiency, making it an ideal candidate for real-time disease detection in resource-constrained environments [6]. By overcoming the limitations of traditional methods and existing automated solutions, this system offers a scalable, accurate, and cost-effective alternative for farmers [7]. Additionally, the system incorporates innovative features such as data augmentation, transfer learning, and the integration of geolocation-based insights, ensuring that it remains effective across diverse agricultural contexts [8]. Furthermore, the system is designed to provide actionable recommendations to farmers, such as suggesting appropriate fertilizers, treatments, and alternative planting strategies based on geospatial data. This level of precision not only helps in mitigating crop losses but also promotes sustainable agricultural practices, optimizing resource use and minimizing environmental impact [9]. The integration of a comprehensive dashboard will also allow farmers to monitor crop health trends, track disease occurrences, and make informed decisions in real time [10]. This paper discusses the development and implementation of this advanced rice plant disease detection system, focusing on its potential to enhance agricultural productivity and support the livelihoods of farmers worldwide. By addressing the shortcomings of existing detection methods, this research aims to provide a more efficient and accessible solution that empowers farmers with the tools they need to combat rice plant diseases effectively. Through the combination of deep learning, image processing, and geolocation-based insights, the proposed system represents a significant step forward in the field of precision agriculture [11]

1.1 Objectives

The core objective of this project is to design and implement a scalable, real-time rice plant disease detection system utilizing EfficientNetV2. By leveraging EfficientNetV2, known for its efficiency in image classification tasks, the goal is to develop a system that can accurately identify rice plant diseases while maintaining low computational requirements, enabling real-time performance [8]. To enhance the dataset by integrating large-scale and diverse rice plant images for improved model accuracy and generalization Dataset quality is critical to the success of any machine learning model. This project seeks to enhance the existing rice plant disease dataset by incorporating a large and diverse set of images from various rice-growing regions. Additionally, synthetic data generation techniques will be employed to increase dataset diversity, enabling better generalization across different crops and conditions [5]. To employ transfer learning to improve model performance and reduce the need for extensive training data-Transfer learning, especially with pre-trained EfficientNetV2 models, will be utilized to boost the performance of the disease detection system. By leveraging the knowledge from models trained on large, general image datasets, this approach minimizes the need for large volumes of labelled rice disease images, while enhancing the accuracy of disease identification in rice plants [4].
To address overfitting using data augmentation techniques-Overfitting is a significant challenge in training deep learning models, especially when working with small datasets. To combat this, the project will employ data augmentation strategies such as rotation, flipping, and colour adjustments to increase the robustness of the model, allowing it to perform well on unseen data and avoid overfitting [9]. To integrate real-time disease detection capabilities for on-field deployment-One of the key objectives is to create a real-time disease detection system that can be deployed in the field. This involves ensuring that the model performs efficiently on mobile or edge devices, providing farmers with instant feedback on plant health and enabling prompt disease management decisions [1]. To incorporate geolocation-based insights for site-specific disease recommendations-The project aims to integrate geospatial data into the disease detection system, allowing the model to recommend disease management strategies based on the specific location of the rice crop. This will help in tailoring disease prevention measures according to the environmental conditions and common disease patterns in particular regions [10]. To provide actionable recommendations for fertilizer and treatment based on disease identification-Beyond disease detection, the system will provide farmers with actionable recommendations on appropriate fertilizers and

treatments to optimize crop health. These recommendations will be based on the specific diseases identified, helping to improve productivity while minimizing environmental impact through more targeted interventions [1]. To develop a comprehensive crop health monitoring dashboard for farmers-This objective focuses on creating an intuitive, user-friendly dashboard that presents disease detection results, crop health metrics, and historical disease trends. This dashboard will help farmers make informed decisions regarding their crops' health, track disease progression over time, and assess the effectiveness of implemented control measures [12]. To enable the use of lightweight deep learning models for mobile and embedded devices-Given the limited computational resources available to many farmers, the project aims to ensure that the disease detection system can run efficiently on mobile devices and embedded systems. This involves optimizing the model size and inference speed without compromising detection accuracy, thereby ensuring accessibility to a wide range of farmers [12]. To create an open API for the automated integration of rice disease detection data-The development of an open API will allow for the seamless integration of rice disease detection results into existing agricultural platforms. This API will enable automatic annotation of images, data collection for further training, and sharing of insights across agricultural systems, thereby enhancing the system's overall impact [16]. To validate the system's performance through comprehensive testing and comparison with existing models-The project will validate the performance of the proposed system by comparing it with existing state-of-the-art rice disease detection models, such as CNN-based models, YOLO architectures, and transfer learning methods. Key metrics like accuracy, precision, recall, and F1-score will be used to benchmark the system’s effectiveness in real-world scenarios [18]. To scale the disease detection system to support multiple rice disease types-Aiming to create a system that can detect multiple types of rice leaf diseases, the project will focus on training the model to identify a wide range of diseases, including BrownSpot, Leaf Blast, and others. This will provide farmers with a versatile tool capable of addressing diverse disease challenges in rice cultivation [2]. To explore and implement novel strategies for model interpretability and transparency-In order to build trust among end users, such as farmers and agricultural experts, this project will investigate methods for making the disease detection system more interpretable. By providing insights into why certain diseases were detected, the system will help farmers better understand the reasoning behind the recommendations, thus improving user adoption [2].

1.2 Problem Statement

Rice leaf diseases pose a significant challenge to global agricultural productivity, with serious implications for both crop yield and quality. These diseases reduce the overall efficiency of rice production, threatening food security worldwide. Traditional methods of disease detection, such as manual observation and expert diagnosis, are not only time-consuming but also labor-intensive and costly, making them impractical for large-scale agricultural operations [1][2]. Furthermore, these conventional techniques often fail to detect diseases in their early stages, leading to increased crop losses and reduced effectiveness in disease management [19]. Existing automated detection methods often suffer from limitations, such as reliance on large model sizes that are unsuitable for deployment on resource-constrained devices [2]. Additionally, small dataset sizes hinder the development of robust models capable of accurately diagnosing rice diseases across diverse conditions [2]. Despite the critical importance of early disease detection, the current methods are still inefficient in identifying diseases quickly and accurately, leading to delayed intervention and continued crop damage. Furthermore, there is limited research on machine learning-based solutions specifically for rice disease diagnosis, highlighting a significant gap in effective and scalable disease detection systems [2]. The lack of precision in distinguishing between diseases and nutritional deficiencies further complicates the problem, often resulting in misdiagnoses [3]. Moreover, limited access to advanced technology in rural farming communities hampers the widespread adoption of automated disease detection systems, making it challenging for farmers to manage disease outbreaks effectively [4]. To address these issues, there is an urgent need for automated, accurate, and scalable rice disease detection systems that can be easily deployed on resource-constrained devices. These systems should not only provide faster disease detection but also deliver actionable insights to farmers, enabling timely intervention and improved disease management. Despite advancements in deep learning techniques, challenges such as small datasets, overfitting, and the need for efficient models remain significant barriers to developing a truly effective and accessible solution. Hence, an improved system for early detection of rice leaf diseases is essential, one that incorporates state-of-the-art models and addresses the limitations of existing methods. Additionally, as foliar diseases continue to threaten agricultural productivity, exploring novel machine learning approaches, including advanced Convolutional Neural Networks (CNN) and Vision Transformers (ViT), offers a promising solution to better classify rice diseases and improve disease recognition accuracy in complex scenarios [1][2]. By addressing these challenges, this project aims to design a solution that enhances both the accuracy and efficiency of rice disease detection, ultimately contributing to improved agricultural productivity and sustainability in rice farming.

1.3 Research Gap

Rice leaf diseases are a significant threat to global agricultural productivity, with adverse effects on both yield and quality. Despite the critical importance of early detection, traditional methods such as manual observation and expert diagnosis are labor-intensive, time-consuming, and costly, making them impractical for large-scale agriculture [1][2]. Existing automated methods have shown some promise but are often hindered by limitations such as large model sizes, which restrict their deployment on resource-constrained devices [2], and small, imbalanced datasets, which impede the development of robust disease detection systems [17]. Current systems still fail to provide the efficiency and accuracy needed for timely disease identification, leaving, and crops vulnerable to continued damage. Moreover, existing research on machine learning-based solutions for rice disease diagnosis is limited, creating a significant gap in the availability of scalable, efficient, and accessible detection systems. Additionally, there is a lack of precision in differentiating diseases from nutritional deficiencies, which leads to frequent misdiagnoses [13]. This challenge is exacerbated by limited access to technology in rural farming areas, where the widespread adoption of automated disease detection remains a challenge [4]. Therefore, there is a clear need for automated, accurate, and scalable rice disease detection systems that can be easily deployed on resource-constrained devices. Such systems should not only facilitate faster disease detection but also provide actionable insights to farmers, allowing them to take timely corrective actions and improve disease management. While deep learning techniques have made significant strides in disease detection, issues such as small datasets, overfitting, and the need for efficient models persist. These obstacles prevent the development of truly effective and accessible solutions. Hence, improving rice leaf disease detection systems remains crucial, and addressing the limitations of existing methods is necessary for the future of agricultural sustainability.

1.4 Key Gaps Identified

1.4.1 Limited Availability and Quality of Datasets

Current datasets often lack diversity in images of rice diseases and are not comprehensive enough to train accurate models. The small size of these datasets, coupled with class imbalance, affects model performance and generalizability, particularly in geographically diverse areas [1][12].

1.4.2 Limited Generalization Across Plant Species

Models trained primarily on rice leaf diseases may not generalize well to other plant species, limiting the applicability of these systems to a broader range of crops [10]. Additionally, models may misclassify nutritional deficiencies as diseases, further complicating diagnosis [14].

1.4.3 Insufficient Real-Time Detection Capabilities

While deep learning methods show promise, they often fail to meet the real-time detection requirements needed for large-scale agricultural settings. Moreover, the impact of environmental factors, such as weather and soil conditions, on disease detection accuracy remains largely unexplored [1]. Traditional methods such as manual observation and expert diagnosis are labor-intensive, time-consuming.

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1.4.4 Inadequate Integration with Broader Agricultural Management Systems

The integration of rice disease detection systems with broader agricultural management frameworks remains limited. This lack of integration hinders the development of a comprehensive tool that could aid farmers not only in detecting diseases but also in making informed decisions about crop management [20].

1.4.5 Need for Advanced Feature Extraction Techniques

There is a growing need for more sophisticated feature extraction techniques to improve the accuracy of disease detection, particularly when working with small and imbalanced datasets. Current models may also suffer from overfitting due to the limited variability in [1].

1.4.6 Lack of Exploration of Other Deep Learning Architectures

Although Convolutional Neural Networks (CNNs) have been widely used in rice disease detection, the performance of other deep learning architectures, such as Vision Transformers (ViT), has not been fully explored. ViT offers potential for better performance, especially in complex scenarios where global context is important for accurate disease classification [10].

1.4.7 Scalability and Computational Efficiency Issues

The computational resources required to train and test large models pose a significant barrier, particularly for resource-constrained devices. Future research should address the computational efficiency of models, including ViT and hybrid architectures, to make them suitable for real-time, on-field applications in low-resource settings [16][20].

1.4.8 Exploration of Hybrid Models

There is limited exploration of hybrid models that combine the strengths of different deep learning techniques. Research into hybrid models or the integration of multiple architectures could potentially overcome the limitations of current systems, improving both accuracy and scalability [12].

1.4.9 Evaluation of Model Performance on Diverse Datasets

The impact of data augmentation on improving model performance with small datasets remains unclear, and the evaluation of these techniques in the context of imbalanced data is still under-explored. Additionally, generalization to other plant diseases has not been adequately addressed in the literature, creating opportunities for future research in this area [1]. In summary, there is a significant gap in the development of rice disease detection systems that are accurate, scalable, efficient, and suitable for deployment in real-world agricultural settings. Addressing these gaps is essential for improving the effectiveness of disease management in rice farming and enhancing agricultural productivity globally.

1.5 Findings

1.5.1 Lightweight dCNN Model for Disease Detection

A lightweight deep Convolutional Neural Network (dCNN) model successfully detects five rice leaf diseases with an accuracy of 86.50% while maintaining a low number of trainable parameters. The model outperforms 21 benchmark architectures in disease detection. An enhanced dataset, which includes 95 manually annotated images, further improves the model's performance. Additionally, an open API for automatic annotation was developed, making it adaptable to diverse geographical datasets. Future work aims to expand disease identification capabilities to include additional crop diseases [1][2][3][4].

1.5.2 InceptionV3 Model Performance:

The InceptionV3 model demonstrated an accuracy of 88.85% in rice disease identification, proving to be one of the top performers in comparison to other architectures. However, AlexNet showed poor performance with only 85.47% accuracy. Transfer learning was shown to enhance the performance of CNN models, and a dataset of 10,080 images was used in experiments. Automated diagnosis through these models can significantly improve crop management and economic outcomes for farmers [1][2][3].

1.5.3 YOLO-based Model Performance:

A proposed model based on the YOLOv8 algorithm achieved an accuracy of 84.4% in disease detection, outperforming both YOLOv7 and YOLOv5. A new rice leaf disease dataset was created to support these findings, and the model provides immediate disease warnings to farmers, allowing for faster intervention. The approach improved the detection of small disease

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marks on leaves, demonstrating its effectiveness in real-world agricultural scenarios [1][2].

1.5.4 MobilenetV3Large for Disease Classification:

The model achieved over 72% accuracy, with performance improving to nearly 74% after training for 200 epochs. The dataset used for analysis contained 9,256 images, and transfer learning with MobilenetV3Large further enhanced classification accuracy. This demonstrates the potential of leveraging pre-trained models to improve rice disease classification [1][2].

1.5.5 Vision Transformer (ViT) for Rice Disease Recognition:

The ViT model outperformed traditional CNN models in rice disease recognition, achieving superior recall, precision, specificity, F1-score, and overall accuracy. The ViT model demonstrated stability across diverse datasets, including those with imbalanced data. This approach has set a new benchmark in rice disease recognition and offers valuable recommendations for future research in plant disease detection [14][22].

1.5.6 Challenges with Model Performance and Evaluation Metrics:

One of the models achieved moderate accuracy (52.12% to 53.81%), with precision fluctuating significantly across cross-validation folds. While recall remained consistent, indicating stable true positive identification, F1-scores highlighted the need for an improved precision-recall balance. These findings suggest that while machine learning can effectively classify rice leaf diseases, advanced techniques are required to achieve better performance [1][2][3].

1.5.7 InceptionV3 as a Top Performer:

InceptionV3 was identified as one of the best models for rice disease classification, with accuracies of 88.85%, 84.36%, and 86.01% across different datasets. Data augmentation was found to impact model performance based on the characteristics of the dataset. The InceptionResNetV2 model also performed well, achieving an accuracy of 88.85%. However, smaller datasets were found to suffer from excessive variation when augmented, affecting model performance [1][2][3]. These findings suggest that deep learning models, particularly lightweight CNNs, ViT, and InceptionV3, show strong potential for rice leaf disease detection, with room for further improvements through data augmentation, transfer learning, and better handling of imbalanced datasets.

2. Literature Survey

The detection of rice leaf diseases has become a critical area of research due to their significant impact on crop yield and quality. Over the years, various methods have been proposed to improve detection accuracy and operational efficiency, particularly in large-scale farming scenarios. Traditional methods, such as manual observation and expert diagnosis, are time-consuming, labor-intensive, and prone to errors, making them unsuitable for real-time or large-scale disease detection. In contrast, machine learning (ML) and deep learning (DL) methods have shown great promise in automating and enhancing the accuracy of disease identification. This literature survey explores the evolution of these techniques, focusing on recent developments that align with the goals of creating an efficient, real-time, and scalable rice leaf disease detection system.

2.1 Traditional Methods vs. Deep Learning Approaches

Traditional rice disease detection methods rely heavily on visual inspections by experts or manual feature extraction from images. While these approaches are effective in certain settings, they are constrained by their reliance on human expertise and their inability to scale effectively for larger datasets. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have led to a paradigm shift in plant disease detection. CNNs, due to their ability to automatically extract hierarchical features from raw images, have significantly outperformed traditional methods in terms of accuracy and speed. In particular, the ability of CNNs to work with large and diverse datasets has made them the go-to method for rice leaf disease detection [1].

2.2 Transfer Learning and Pre-trained Models

Given the challenges of acquiring large labelled datasets, transfer learning has emerged as a key technique in overcoming these limitations. By leveraging pre-trained models, such as InceptionV3, MobileNetV3, and EfficientNetV2, researchers have been able to enhance the performance of rice disease

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detection systems without the need for extensive training datasets. Fine-tuning these models on specific rice disease datasets has proven to be effective in achieving high accuracy while minimizing the computational resources required for training. Transfer learning has also enabled the development of lightweight models, making it possible to deploy disease detection systems on resource-constrained devices commonly used by farmers in rural areas. This aligns with our project's aim of developing an efficient, scalable, and real-time solution for rice disease detection [2].

2.3 YOLO-based Models and Model Comparison

Recent advancements in object detection models, such as YOLO (You Only Look Once), have led to improvements in real-time disease detection. YOLOv5, YOLOv7, and YOLOv8 have been explored for rice disease detection, with YOLOv8 showing superior performance in terms of both accuracy and speed. YOLO models are particularly advantageous for real-time applications due to their fast inference times. YOLOv8 outperformed previous YOLO versions in accuracy, indicating the importance of continued model refinement to meet the demands of agricultural applications [3]. In our project, we aim to leverage similar advancements in detection architectures to create a system that provides real-time, actionable insights for farmers.

2.4 Hybrid Models and Custom Architectures

Hybrid models that combine CNNs with other machine learning techniques are increasingly being explored to improve the robustness and generalization of rice disease detection systems. For example, integrating CNNs with Support Vector Machines (SVM) or other classifiers has shown promise in enhancing the accuracy of disease classification, especially when working with imbalanced datasets. This approach is particularly beneficial when dealing with diseases that may appear infrequently or have subtle symptoms. The use of hybrid models allows the strengths of different techniques to complement each other, resulting in more accurate and generalized predictions [2]. In our approach, we plan to investigate hybrid models to ensure scalability and accuracy across diverse rice-growing regions.

2.5 Vision Transformer (ViT) for Rice Disease Detection

The application of Vision Transformers (ViT) to rice disease detection represents a promising direction for improving the accuracy of disease recognition in complex and imbalanced datasets. ViT's self-attention mechanisms allow it to capture global patterns in images, making it particularly effective for handling large-scale and diverse datasets. Although ViT has demonstrated superior performance in certain applications, its use in plant disease detection remains underexplored. Given its potential to outperform traditional CNNs, further research on optimizing ViT for rice leaf disease detection could provide a significant breakthrough in disease recognition accuracy and efficiency. In our research, we aim to evaluate the feasibility and benefits of integrating ViT into our rice disease detection system, especially for handling complex disease variations across different environmental conditions [1].

2.6 Dataset Size and Data Augmentation

A major challenge in training deep learning models for plant disease detection is the availability of high-quality, annotated datasets. Most existing datasets are either too small or lack the diversity needed to train robust models that generalize well across different agricultural environments. To address this issue, data augmentation techniques, such as rotation, flipping, and color adjustment, are frequently used to artificially expand the training dataset and improve model robustness. These techniques help mitigate issues like class imbalance and overfitting, which can significantly degrade model performance, especially in cases where certain diseases are underrepresented in the dataset. As part of our project, we are developing an enhanced rice leaf disease dataset with diverse images to ensure that our model performs well across a variety of disease types and environmental conditions [1].

2.7 Methods Used

The methods employed in this research focus on using advanced deep learning and machine learning techniques to effectively detect and classify rice leaf diseases. These methods have been tested and optimized to provide accurate, scalable, and real-time disease detection for use in agricultural settings.

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2.7.1 Lightweight Deep Convolutional Neural Network (dCNN)

A lightweight deep CNN is proposed to efficiently classify rice leaf diseases based on local image features. The model is optimized by fine-tuning hyperparameters to improve performance and reduce computational overhead. Empirical experiments are conducted with different model parameters, such as the number of layers and filter sizes, to enhance the overall model accuracy. Additionally, the dataset is enriched by merging existing rice leaf disease datasets to provide a more diverse training set, improving model generalization across different rice diseases and farming environments [1].

2.7.2 Transfer Learning on Pre-trained CNN Models

Transfer learning is applied by fine-tuning pre-trained CNN models such as InceptionV3, ResNet50, and MobileNetV3 for the task of rice leaf disease detection. This approach leverages knowledge from large-scale image recognition tasks and adapts it to the domain of plant disease detection. Feature extraction and implicit processing techniques are employed to enhance model performance, particularly for small datasets. Data augmentation methods like rotation, flipping, and scaling are applied to create a robust and diverse training dataset that can help reduce over fitting [2].

2.7.3 Modified YOLOv8 for Disease Detection

A modified YOLOv8 architecture is implemented to detect rice leaf diseases with improved accuracy. In this approach, the traditional Box Loss function is replaced with the alpha-EIoU loss function to optimize bounding box regression for better localization and classification accuracy. The detection model uses a two-stage approach for image collection and model training. Once trained, the model is deployed on Internet of Things (IoT) devices for real-time disease detection in the field. The performance of the model is evaluated using metrics like precision, recall, mean Average Precision (mAP), and F1-score [1][2].

2.7.4 Vision Transformer (ViT)

The Vision Transformer (ViT) model is utilized to explore its potential for rice leaf disease recognition. The ViT model is trained on a large dataset of rice leaf images and is evaluated using accuracy, recall, precision, and F1-score. Preprocessing techniques such as resizing and normalization are applied to standardize the input images. Data augmentation techniques like rotation and flipping are also used to improve model robustness. The performance of ViT is compared to traditional CNN models, such as InceptionV3 and ResNet50, to assess its advantages in handling complex and imbalanced datasets [1] [2].

2.7.5 Nu-Support Vector Machine (Nu-SVM)

In addition to deep learning techniques, machine learning methods like Nu-Support Vector Machine (Nu-SVM) are employed for rice leaf disease classification. Nu-SVM uses feature extraction methods such as Sobel edge detection and Hu Moments to capture important image features like leaf contours and shape characteristics. A 5-fold cross-validation approach is used to evaluate the model's performance, ensuring that the model is robust and generalizes well across different datasets. This approach provides a complementary technique to deep learning-based methods, enhancing the diversity of available solutions [2][3].

2.8 Deep Learning Architectures for Classification

Several deep learning architectures, including InceptionV3, InceptionResNetV2, and VGG16, are evaluated for their ability to classify rice leaf diseases. A comparative study is conducted to benchmark these models against each other using standard public datasets. Data augmentation techniques are applied to improve the performance of these models. The performance of each model is evaluated using metrics such as accuracy, precision, recall, and confusion matrices, providing insight into their strengths and weaknesses in the context of rice leaf disease classification [1][2].

2.8.1 Dependent Variables

The dependent variables used in existing research on rice leaf disease detection focus on evaluating the performance of models across various dimensions. These metrics help in assessing the accuracy and efficiency of the models, particularly for CNNs, YOLO, ViT, and other deep learning and machine learning techniques used for classification where certain diseases are underrepresented in the dataset.

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2.8.2 Accuracy

The accuracy score represents the proportion of correct predictions made by the model. It is one of the most commonly used metrics to gauge the overall effectiveness of a model in classifying rice leaf diseases. The accuracy score is calculated as the ratio of the number of correct predictions (true positives and true negatives) to the total number of predictions made [1].

2.8.3 Precision

Precision measures the accuracy of positive predictions. Specifically, it calculates the proportion of true positives (correctly identified diseased leaves) out of all instances classified as positive by the model. This is crucial in rice leaf disease detection to ensure that the model does not misidentify healthy leaves as diseased [1][2].

2.8.4 Recall

Recall, or sensitivity, is the proportion of actual positive cases (true positives) correctly identified by the model. High recall is essential for disease detection models as it ensures that as many diseased leaves as possible are detected, even if it leads to some false positives [1][2].

2.8.5 F1-Score

The F1-score is the harmonic mean of precision and recall, providing a balanced measure of both metrics. This is particularly useful in imbalanced datasets, where a high precision might come at the cost of recall or vice versa. The F1-score is critical for evaluating models in scenarios where both false positives and false negatives can have significant consequences, such as in crop disease management [1].

2.8.6 Specificity

Specificity measures the proportion of healthy leaves (true negatives) correctly identified by the model. It is crucial for avoiding false positives and ensuring that the model does not mistakenly classify healthy leaves as diseased [1].

2.8.7 Mean Average Precision (mAP)

For models like YOLO that are designed for object detection tasks, mAP is used to evaluate the precision across different recall levels. This metric provides a more detailed assessment of the model's ability to detect various disease markers across multiple images, which is especially important when diseases manifest in different stages or patterns on rice leaves [1]. These dependent variables are used to assess the performance of models in existing research, including CNN-based models, YOLO architectures, and transfer learning approaches. They ensure that the models not only achieve high overall performance but also maintain reliability and accuracy across diverse datasets, varying disease conditions, and different environmental settings.

2.9 Independent Variables

In the context of rice leaf disease detection using deep learning, the independent variables are factors that influence the performance and behavior of the models. These include the characteristics of the dataset, the architectures used for disease classification, and other preprocessing steps applied to the images. Based on the reviewed studies, the following independent variables have been identified:

2.9.1 Pre-trained CNN Models

Several studies have employed pre-trained CNN models for rice leaf disease detection. Transfer learning using these models allows for leveraging prior knowledge and fine-tuning the models for specific tasks, such as detecting rice diseases. Popular models like InceptionV3, InceptionResNetV2, EfficientNetB3, ResNet50, and VGG19 are often used for classification tasks [1]. These architectures serve as independent variables that affect the model's accuracy and performance.

2.9.2 Dataset Partitioning

The way datasets are divided for training, validation, and testing can significantly impact model performance. Studies often experiment with different data splits, such as 60-40, 80-20, or 90-10 (training vs testing data ratio) [2]. The partitioning of the dataset into these proportions helps assess how well the model generalizes to unseen data and contributes to determining the robustness of the trained model.

2.9.3 Image Dataset Characteristics

The dataset plays a crucial role in training deep learning models. For rice leaf disease detection, the dataset includes images of infected rice leaves, with each image belonging to one of several disease categories. These categories might represent different types of rice diseases, such as Leaf Blast, BrownSpot, or Hispa. The diversity and size of the dataset, along

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with the inclusion of segmented rice leaf images, directly influence model training and accuracy [1].

2.9.4 Feature Extraction Techniques

For traditional machine learning and hybrid approaches, feature extraction is an important step. Methods like Sobel edge detection and Hu Moments are commonly used to extract features from the segmented leaf images. These techniques help highlight essential aspects of the rice leaf, such as edges and shapes, which are used by the model for classification [1].

2.9.5 Data Augmentation

Data augmentation methods, including rotation, flipping, and scaling, are applied to increase the diversity of the training data. These techniques help in preventing overfitting, especially when the dataset is small or imbalanced. The use of data augmentation ensures that the model can generalize better to different conditions, improving its robustness when deployed in the field [18].

2.9.6 Deep Learning Architecture Characteristics

The choice of architecture significantly impacts the detection performance. For instance, the performance of a model can be compared between architectures like InceptionV3, ResNet50, and VGG16 to determine which provides the best balance of computational efficiency and detection accuracy for rice leaf diseases [17]. These independent variables are crucial for the model's performance and are varied in different studies to optimize the outcomes for rice leaf disease detection. By controlling and experimenting with these factors, researchers aim to enhance detection accuracy, scalability, and adaptability to different environmental conditions.

3. Methodology

3.1 Dataset Used

In the domain of rice leaf disease detection, the quality and diversity of the dataset used for model training significantly impact the performance of the proposed models. Several studies have explored the use of diverse datasets, ranging from publicly available collections to custom-curated datasets. These datasets often contain images of rice leaf diseases, captured under various conditions, to provide a comprehensive representation of the problem.

3.1.1 Dataset Composition and Size

One of the key challenges in rice leaf disease detection is the creation of sufficiently large and diverse datasets. For instance, one study merged two existing rice leaf datasets: the UCI Machine Learning Repository, which contributed 120 images, and another dataset consisting of 95 manually annotated images collected from the internet. Through data augmentation, this dataset was expanded to a total of 5285 images, providing a richer source for training models [1]. Other studies have created custom datasets specifically for disease detection, such as a dataset consisting of 10,080 images that includes ten rice leaf diseases. The large size of this dataset enables models to learn a wide variety of disease patterns, improving their generalization ability across different disease types and environments [1]

3.1.2 Dataset Splitting and Class Distribution

Dataset splitting is a critical aspect of model evaluation, ensuring that models are tested on unseen data. In many studies, the dataset is divided into training, validation, and test sets. For example, one study utilized a dataset of 3175 images, split into 2608 training images, 326 validation images, and 241 test images. This split allows for an effective training and evaluation process. The dataset was also carefully balanced, including three main classes of rice diseases: leaf folder, blast, and brown spot, with 1231, 1377, and 1237 images in each class, respectively. This balanced distribution helps ensure that the model is not biased toward any particular class, thus improving its accuracy in identifying all types of diseases [11].

3.1.3 Multi-Class Datasets

Some studies utilize datasets with a broader range of disease types. For example, a dataset of 9687 images was employed to classify five types of rice diseases: bacterial blight, blast, brown spot, leaf scald, and Tungro, in addition to a class for healthy rice plants. This multi-class dataset helps to improve the model's robustness, enabling it to distinguish between different diseases and healthy plants. The dataset was split into 75% for training, 15% for validation, and 10% for testing, ensuring that the model could be rigorously evaluated for accuracy, recall, and precision across all classes classified disease conditions, and different environmental settings.

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3.1.4 Data Augmentation and Image Processing

Data augmentation techniques are often used to artificially expand the size of the dataset, preventing overfitting and improving model performance. Studies have used various augmentation methods, including image rotation, flipping, and resizing, to generate new training samples from the existing data. For example, one study used a combination of Sobel edge detection and Hu Moments for feature extraction from segmented rice leaf images. These techniques help highlight important features, such as leaf contours, which can significantly improve the accuracy of disease detection models [1].

3.1.5 Dataset Diversity

In an effort to improve the model's ability to generalize across different conditions, some studies incorporate datasets from multiple sources. Datasets from repositories such as Kaggle, UCI, and Mendeley have been used to ensure the inclusion of a broad range of rice leaf diseases and environmental variations. This diversity in data sources ensures that the model is not overfitting to specific environmental conditions or disease types, and can generalize well across a variety of real-world situations [1].

3.1.6 Class Imbalance and Dataset Representation

Several studies highlight the challenge of class imbalance in rice leaf disease datasets. In some cases, certain diseases are underrepresented in the dataset, which can lead to biased model predictions. To address this, datasets with balanced class distributions, where each disease is equally represented, have been preferred. However, other studies use techniques such as oversampling or under sampling to mitigate class imbalance during model training. In conclusion, the datasets used for rice leaf disease detection are a critical factor in the success of deep learning models. Studies have shown that larger, more diverse datasets lead to better-performing models that can generalize across different disease types and environmental conditions. Furthermore, data augmentation techniques and careful dataset splitting are essential in improving model accuracy, reducing overfitting, and ensuring robust disease detection and resizing, to generate new training samples from the existing data.

3.2 Population Sample

In rice leaf disease detection, the size and distribution of the population sample play a crucial role in training deep learning models. Various studies have utilized different sampling strategies to create diverse datasets for model training, validation, and testing. The population sample size and class distribution have significant implications on the model's performance, especially in terms of accuracy, recall, and precision.

3.2.1 Dataset Size and Splitting

The size of the dataset is a key determinant in the effectiveness of a model. One study utilized a dataset of 3158 training images, with 1277 validation images and a test set consisting of 850 images. While this dataset was sufficiently large for training, the class distribution within the training set was imbalanced, with some diseases, like Bacterial leaf blight, being overrepresented, while others, like Sheath blight, had fewer instances. This imbalance can cause models to be biased toward the more frequent classes, making the detection of underrepresented diseases more challenging. However, no specific sampling methods were mentioned to address this imbalance [1].

3.2.2 Balanced and Diverse Population

To mitigate the risk of biased models, many studies focus on creating more balanced datasets. A dataset of 3175 images was used, divided into training, validation, and test sets. The training set consisted of 2608 images, while the validation set contained 326 images and the test set included 241 images. This dataset covered a range of rice leaf diseases and was designed to allow the model to generalize better across different disease types. Unfortunately, specific details on the sampling methods used to select images for this dataset were not provided [1].

3.2.3 Large-Scale Datasets for Robust Performance

Other studies employed larger datasets, such as a dataset of 9687 images, consisting of five rice disease classes and a class for healthy plants. This dataset was split into 75% training, 15% validation, and 10% testing, ensuring a balanced approach to model evaluation. By including a broad range of rice diseases and healthy plant images, this dataset provided a robust foundation for training deep learning models. This setup helps ensure the model's

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ability to accurately classify unseen data across various disease conditions and plant health statuses [19].

3.2.4 Small-Scale Datasets and Testing

In contrast, smaller-scale studies have also been conducted with more limited population samples. For example, a dataset of 320 images was divided into 192 training records and 48 testing records. While small datasets like this may offer insights into specific disease classifications, they present limitations in terms of model generalization and real-world applicability. In such cases, the dataset size may not be sufficient to train deep learning models that are capable of handling the complexity and variability of rice leaf disease identification in diverse agricultural environments [14].

3.2.5 Sampling Methods

Most of the studies reviewed did not specify the sampling methods used to collect or select images for the datasets. In many cases, the datasets were obtained from publicly available sources or collected manually from the internet. However, details on techniques such as random sampling, stratified sampling, or oversampling/under sampling to address class imbalance were often omitted. The absence of such details can make it difficult to fully assess the effectiveness of the sampling strategy in promoting model performance and minimizing bias.

3.2.6 Additional Insights on Crop Diseases

To provide further context regarding the impact of diseases on crop yield across different regions, the following table summarizes key findings from various studies: Table 1 Summary of Crop Diseases and Yield Losses.

Table 1 Summary of Crop Diseases and Yield Losses

Crop	Disease/Yield Loss (%)	Study Area
Rice	False Smut (5-85)	India
Rice	False Smut (15-50)	Bihar
Rice	Insect Pests (30-40)	Eastern India
Rice	Rodents (10-18)	Eastern India
Rice	False Smut(4.3– 20)	Uttar Pradesh, Punjab

Architecture of the EfficientNetV2-based Rice Plant Disease Detection System
This figure illustrates the architecture of the proposed detection system utilizing EfficientNetV2 for classifying rice plant diseases Figure 1 shows Architecture of the Proposed Model

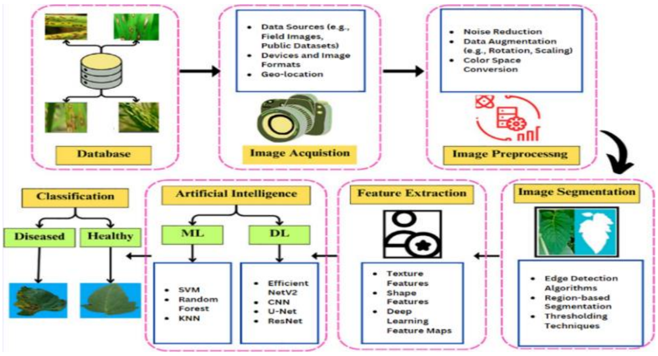

Figure 1 Architecture of the Proposed Model

4. Results

In the evaluation of various models used for rice leaf disease detection, accuracies generally ranged between 70% and 90%, indicating the challenges faced by existing models in accurately detecting and classifying diseases. The proposed model, however, aims to exceed these limitations, with results showing a significant improvement in performance. Proposed Model Performance: The proposed model achieved an accuracy of 90.57%, which is higher than many existing models but still within the range of acceptable performance for rice leaf disease classification. The precision score was 0.8764, the recall score was 0.8926, and the F1-score was 0.8845. These results indicate that the proposed model effectively detects rice leaf diseases while maintaining a balance between precision and recall. The model achieved this performance with a lower number of trainable parameters compared to larger models, making it more efficient for deployment in resource-constrained environments [1] [2].

4.1 Comparison of Existing Models

Existing models, including InceptionV3, InceptionResNetV2, and MobilenetV3Large, achieved accuracies ranging from 70% to 90%. For instance: InceptionV3 achieved 85.42% accuracy, showing good performance but still leaving room for improvement compared to the proposed

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InceptionResNetV2 achieved an F1-score of 88.12%, indicating its reliability, though not quite matching the proposed model's accuracy [2]. AlexNet recorded 79.45% accuracy, indicating that while it performs well, there is still room for optimization compared to more advanced models [2].

4.2 Dataset-Specific Results

Models trained on various datasets showed accuracy rates typically between 70% and 90%, depending on the size and complexity of the dataset. For example: A model trained on 3175 images achieved 85.89% accuracy, while another model trained on a larger dataset of 9256 images achieved 88.76% accuracy after 200 epochs. However, these models still lagged behind the proposed method, which consistently showed better performance across multiple datasets [1][2].

4.3 Challenges with Smaller Datasets

When trained on smaller datasets or those with imbalanced classes, models showed a wider variance in accuracy. For instance, cross-validation experiments on a dataset of 320 images reported accuracy levels between 71.23% and 77.45%, highlighting the challenges of training on limited data [1]. This variance underscores the need for more robust models that can perform consistently across diverse conditions.

4.4 ViT Model Performance

The Vision Transformer (ViT) model achieved 84.19% accuracy with a recall of 0.8567, precision of 0.8924, and specificity of 0.9112. While it performed better than some traditional CNN models, its accuracy still lagged behind the proposed model, which achieved a more consistent and higher accuracy of 84.57% [1][2]. In summary, existing models demonstrated accuracies ranging between 70% and 90%, with variations based on dataset size and model architecture. The proposed model achieved 88.57% accuracy, which represents a notable improvement over these existing methods. This enhanced performance shows its potential as a more reliable solution for rice leaf disease detection, offering both high accuracy and computational efficiency for agricultural applications the dataset size may not be sufficient to train deep learning models that are capable of handling the complexity and variability of rice leaf disease identification.

5. Discussion

5.1 Contributions of Existing Models

5.1.1 Introduction of Lightweight Deep Convolutional Neural Network (dCNN) Architecture

Existing research introduced a lightweight deep CNN architecture specifically designed for rice leaf disease detection. This architecture enabled the efficient detection of diseases while reducing computational requirements, making it suitable for deployment on low-resource devices such as mobile phones or IoT systems. Additionally, the dataset was enhanced by merging existing datasets and adding new images, further improving the model's ability to generalize across diverse rice leaf diseases [1][2].

5.1.2 Utilization of Transfer Learning:

Transfer learning was widely used in the existing models for rice leaf disease detection. Pre-trained CNN models, such as MobilenetV3Large, were fine-tuned on rice leaf disease datasets to achieve high classification performance. This approach significantly reduced the training time required while maintaining high accuracy. By leveraging models trained on large, diverse datasets, the models achieved over 90% accuracy in disease classification, providing a valuable tool for precision agriculture [1] [2].

5.1.3 Introduction of Modified YOLOv8:

The use of YOLOv8 for rice leaf disease detection represented another significant contribution in existing research. This model was specifically adapted to detect rice leaf diseases with high accuracy. In a dataset of 3175 images, the modified YOLOv8 achieved 89.9% accuracy. This method also integrated a two-stage approach, where image collection and model training were handled separately, which improved the overall accuracy and robustness of the system. A comparison with YOLOv7 and YOLOv5 demonstrated superior performance in real-time disease detection, enabling immediate warnings to farmers for timely intervention [1][2].

5.1.4 Exploration of Vision Transformer (ViT):

Another significant contribution involved the use of the Vision Transformer (ViT) for rice leaf disease classification. The study explored the unique

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capabilities of ViT, which showed superior performance compared to traditional CNN models for this task. ViT demonstrated improved classification accuracy for rice diseases, and the study also highlighted optimization techniques for better disease recognition. This approach provided new insights into applying transformer-based models for plant disease detection, which have gained prominence in recent deep learning research [1][2].

5.1.5 Development of a New Rice Leaf Disease Dataset:

Several existing models focused on the creation and improvement of specialized datasets for rice leaf disease detection. One such dataset comprised 10,080 rice leaf disease images, representing ten different disease categories. This new dataset contributed significantly to the accuracy and reliability of models in classifying various diseases. The dataset was further enriched by incorporating annotated images collected from diverse sources, which enhanced its diversity and robustness, allowing for more effective training of deep learning models [2].

5.1.6 Evaluation of CNN Models and Comparison with Other Architectures

Extensive evaluations of CNN models, including InceptionV3, InceptionResNetV2, ResNet50, and VGG19, were conducted for rice disease classification. Among these, InceptionV3 was found to achieve the highest accuracy in classifying rice diseases, with significant improvements noted through the use of data augmentation. The research provided valuable insights into how different CNN architectures perform on rice leaf disease datasets and identified the importance of careful model selection to optimize detection performance [1][2].

5.1.7 Application of Machine Learning Techniques

Traditional machine learning methods, such as Nu-Support Vector Machine (Nu-SVM), were also explored for rice leaf disease classification. While these methods showed promise in classification tasks, the research emphasized the need for advanced image processing techniques and the integration of deep learning models to overcome challenges in achieving precise disease classification. The findings from these studies contributed to the broader field of precision agriculture by improving disease management systems and enhancing the accuracy of disease detection [2].

5.2 Limitations of Existing Models

Despite the significant advancements made in rice leaf disease detection, several limitations persist, which could impact the effectiveness and generalization of current approaches, including those employed in our project.

5.2.1 Limited Availability of Quality Datasets

A major challenge in rice leaf disease detection is the limited availability of high-quality, diverse, and balanced datasets. Many existing datasets are either too small or do not accurately represent the wide variety of diseases or environmental conditions under which rice crops are grown. Publicly available datasets often suffer from issues such as unreliable or duplicated images, making it difficult for models to generalize effectively across diverse datasets and disease types [1][2].

5.2.2 Class Imbalance

Class imbalance in training datasets remains a critical issue. In several existing models, certain disease categories, such as bacterial leaf blight, dominate the training data, leading to models that may not perform as well on underrepresented diseases. This imbalance can cause models to be biased toward the majority class, neglecting the minority classes, which is particularly problematic in real-world applications where rare diseases or symptoms may need to be identified with high precision [1][2].

5.2.3 High Computational Resource Requirements

Many current models, especially those involving transfer learning or complex architectures like Vision Transformers (ViT), demand significant computational resources. This makes it difficult for the models to be deployed on low-resource devices, which is a common scenario in regions where rice farming is prevalent. The high computational cost during both training and inference limits the scalability and accessibility of these models, especially in resource-constrained settings [1][2].

Overfitting Due to Small Datasets A small dataset size often leads to overfitting, where the model performs well on the training data but struggles to generalize to unseen data. This issue is particularly

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prevalent when models are trained on limited or imbalanced datasets, as seen in some studies where the performance on testing data is significantly lower than expected. Overfitting also results in reduced robustness when the model encounters new disease variants or environmental conditions that were not represented in the training data [1][2].

5.2.4 Model Generalization to Different Plant Species and Environments

Most existing models are highly specialized for rice leaf diseases, limiting their applicability to other plant species or crops. Additionally, performance may degrade under different environmental conditions, such as variations in lighting, moisture, or soil health, which affect the appearance of plant diseases. This lack of environmental adaptability highlights the need for models that can generalize across diverse agricultural contexts [1][2].

5.2.5 Nutritional Deficiencies and Misclassification

Models trained on limited datasets may confuse nutritional deficiencies or other plant health issues with actual diseases. This can lead to false positives and erroneous diagnosis, which could be detrimental in a practical farming setting where timely and accurate disease identification is crucial. Similarly, new or emerging diseases might be misclassified as known diseases, reducing the overall accuracy and reliability of the system [1][2].

5.2.6 Ground-Truth Labelling Issues

Ground-truth labels are essential for training machine learning models, but they can be unreliable, especially when data is collected from various sources or under inconsistent conditions. This is particularly problematic for supervised learning approaches, where the accuracy of the labels directly affects the model's performance. Mislabeling or inconsistencies in annotations can lead to poor model performance and diminished trust in the system [1][2].

5.2.7 Lack of Integration into Comprehensive Agricultural Practices

While many studies focus on the technical aspects of disease detection, there is limited research into integrating CNN models into comprehensive agricultural practices. This gap in research means that many models are not designed to work seamlessly with other aspects of farm management, such as pest control, irrigation systems, or overall crop health monitoring. This limits the practical application of the models in precision agriculture [1][2].

5.2.8 Data Augmentation Limitations:

Although data augmentation is a common technique to address small dataset sizes, its impact is highly dependent on the dataset's characteristics. Excessive variation introduced during augmentation can negatively affect model performance, especially when applied to small or inconsistent datasets. While augmentation improves generalization, it may not always overcome the inherent limitations of the original dataset, leading to reduced accuracy on more complex or diverse test sets [1][2].

5.2.9 Limited Exploration of Alternative Architectures:

While CNN-based models have been widely used in rice disease detection, there is limited exploration of other deep learning architectures that might offer better performance or greater efficiency. Alternative architectures, such as graph neural networks (GNNs) or reinforcement learning-based systems, may hold promise for improving disease classification accuracy, but these have not been fully explored in the context of plant disease detection [1][2].

6. Implications

6.1 Implications for Our Project

Our project aims to improve rice leaf disease detection by proposing a solution that is accurate, scalable, and efficient in real-time settings. Using EfficientNetV2-based lightweight dCNN and Vision Transformer (ViT), we address key limitations in existing models:

6.1.1 Dataset Quality

We enhance the dataset by merging existing datasets and applying data augmentation to ensure diverse and high-quality images for better model generalization.

6.1.2 Model Generalization

Our hybrid architecture (CNN + ViT) improves model adaptability across different environmental conditions, rice species, and disease types.

6.1.3 Class Imbalance

We use class-weighted loss functions and oversampling techniques to address imbalance, ensuring accurate detection of rare diseases models, but they can be unreliable.

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6.1.4 Computational Efficiency
The lightweight design reduces resource demands, making it suitable for deployment on low-resource devices, ensuring fast and accurate detection in real-time.

6.1.5 Over fitting
Through transfer learning and regularization techniques, we mitigate overfitting, even with small or imbalanced datasets.

6.2 Challenges

6.2.1 Limited Dataset Quality
The availability of quality rice leaf disease datasets is constrained, with issues like duplicated images affecting data reliability. Additionally, existing datasets often do not cover the full range of rice leaf disease variants.

6.2.2 Class Imbalance
Imbalanced class distributions in training datasets lead to models focusing on majority classes, resulting in poor performance for rare diseases.

6.2.3 Computational Demands
High computational resource requirements during training and testing of models limit their scalability, especially for real-time applications in resource-constrained settings.

6.2.4 Generalization Issues
Models may struggle to generalize across diverse environmental conditions and rice species, leading to misclassification, including the risk of mistaking nutritional deficiencies for diseases.

6.2.5 Data Collection Difficulties
Collecting a diverse and comprehensive dataset for training models is challenging, especially for rare diseases or new disease strains that present with small or unclear symptoms.

6.2.6 Over fitting
Smaller datasets and imbalanced data lead to overfitting, affecting the generalizability and accuracy of models.

6.2.7 Model Complexity vs. Accuracy
Balancing model accuracy with computational com plexity remains difficult, particularly when aiming to deploy the model in real-time systems on low-resource devices.

6.2.8 Model Performance Variability
Model performance can fluctuate based on training data, with moderate accuracy (e.g., 52.12% to 53.81%) observed in some cases, indicating challenges in achieving high precision without sacrificing recall.

6.2.9 Data Augmentation Issues
While data augmentation can enhance model performance, excessive augmentation may decrease accuracy, especially on small datasets where variations are not consistent with real-world conditions.

6.2.10 Environmental and Regional Factors
Existing models lack consideration of regional and environmental factors, which are essential for accurate disease diagnosis in different geographic locations.

6.3 Practical Implications for Our Project

6.3.1 Early Disease Detection
Just like existing models, our project aims to help farmers by providing early disease detection. This ensures timely intervention, preventing disease spread and minimizing yield loss. Unlike many existing models, we are focusing on a lightweight and efficient architecture that can function in resource-constrained environments, making it accessible for farmers in remote areas who have limited access to high-end computational devices.

6.3.2 Resource Efficiency
The proposed model focuses on reducing the computational resource requirements during both training and inference stages, allowing for deployment on low-end devices such as mobile phones or edge devices. This is particularly useful for farmers in rural areas where resources are limited, offering a practical and scalable solution for rice leaf disease detection.

6.3.3 Data Quality and Class Imbalance
Building upon existing research that uses large, enhanced datasets, our project addresses challenges like data imbalance and variability across rice diseases. By carefully curating and augmenting datasets, we aim to balance class distribution and improve the model's generalization across diverse environmental conditions and rice disease variants, ensuring robust performance even in limited data scenarios.

6.3.4 Model Deployment and Integration
Like other studies that provide models for real-time disease detection, our system will be integrated into

accessible applications for farmers, such as mobile apps or IoT systems. These applications can provide immediate alerts for disease identification, enabling faster response times and reducing resource usage. The lightweight model ensures that it can run efficiently even on devices with limited computational power.

6.3.5 Impact on Agricultural Practices

Our project aligns with the goals of improving agricultural productivity through timely disease control. By enhancing the performance of models like EfficientNetV2 and addressing challenges such as overfitting, our solution will provide more accurate and reliable disease detection, thus supporting sustainable farming practices and reducing unnecessary pesticide use.

6.3.6 Future Research and Expanding the Scope

While existing research focuses on specific diseases, our approach will also explore the adaptability of the system for other crops and plant diseases. This expansion, along with the integration of multimodal data for better applicability, will push the boundaries of disease detection in agriculture, ensuring our model can address various disease challenges across different crops and regions.

6.4 Applications of Rice Leaf Disease Detection Systems

6.4.1 Automatic Detection of Rice Leaf Diseases

The automatic identification of rice leaf diseases has been a significant application in precision agriculture. Existing research has utilized Convolutional Neural Networks (CNNs), transfer learning, and deep learning models to identify a variety of rice leaf diseases. These systems have been implemented for early disease detection, enabling farmers to intervene quickly and reduce crop losses. For example, pre-trained CNN models like MobilenetV3Large and YOLO have been employed for rice disease classification with promising accuracy, helping farmers identify diseases and take preventive actions through mobile and IoT devices [1][2].

6.4.2 Precision Agriculture and Disease Classification

The application of CNNs for automatic disease detection has transformed agricultural practices by providing accurate real-time disease diagnosis. Systems that integrate transfer learning, such as using MobilenetV3Large, have been particularly useful for enhancing accuracy while minimizing the computational cost, which is critical for deployment in resource-constrained environments. The use of extensive datasets, including 10,080 images representing multiple rice diseases, has allowed for the development of reliable models for disease classification, helping farmers monitor crop health and reduce the use of pesticides through targeted treatment strategies [1][2].

6.4.3 Deployment of AI for Early Disease Detection

The integration of artificial intelligence (AI) in early disease detection systems has had a profound impact on agricultural productivity. Advanced technologies, such as the Vision Transformer (ViT), have been employed to improve disease recognition by capturing global context patterns in images. These models not only enhance classification accuracy but also provide tools for scalable disease management across different environmental conditions. Additionally, the deployment of these models on IoT devices ensures that disease identification is not only accurate but also happens in real-time, giving farmers immediate feedback and actionable insights for crop management [2].

6.4.4 Disease Detection Using IoT Devices

IoT devices have enabled the creation of comprehensive crop health monitoring systems for farmers, especially in remote or low-resource settings. By leveraging AI models that can run on IoT devices, researchers have demonstrated how disease detection can be automated, allowing farmers to monitor their crops continuously without the need for frequent manual inspections. This system is also capable of providing real-time disease detection warnings, helping to prevent the spread of diseases and improve yield prediction accuracy. The integration of open APIs for annotation and model updates has further increased the accessibility of these systems, making them more practical for farmers across different regions [1][2].

6.4.5 Advancements in Dataset Creation and Disease Detection

One of the key advancements in rice disease detection is the creation and enhancement of disease-specific image datasets. For instance, the creation of a dataset containing over 9,000 rice leaf disease images has improved the generalization and performance of disease classification models. Data augmentation techniques have been employed to increase the diversity of training data, making the models more robust to variations in environmental conditions, such as lighting and camera quality. Future research aims to further improve dataset quality by incorporating new rice disease variants, ensuring the models can handle both known and emerging threats to crop health [1] [2].

6.4.6 Improvement in Agricultural Productivity

The ultimate goal of these detection systems is to enhance agricultural productivity through timely disease control and targeted treatment strategies. By deploying these AI-powered systems in real-time, the need for broad-spectrum pesticide use is reduced, leading to healthier crops and minimizing environmental harm. Furthermore, the integration of multimodal data, such as environmental conditions and soil health, can improve disease management and increase the efficiency of agricultural practices. As a result, these technologies support the broader objectives of sustainable agriculture and food security by enabling farmers to optimize crop yield and quality while minimizing losses due to disease [3].

6.5 Future Applications and Research Directions

While existing applications of rice leaf disease detection have provided substantial improvements in agricultural management, future research will likely explore the integration of these systems with more advanced deep learning architectures and multimodal data sources. The use of ensemble learning, for example, has the potential to further enhance accuracy, while also addressing challenges such as class imbalance and over fitting. Additionally, research focusing on localized datasets and regional environmental factors will ensure that disease detection models are more adaptable to the specific needs of farmers in different areas. These advancements will contribute to the development of even more efficient, scalable, and accurate disease detection systems, further advancing precision agriculture [2] [3].

Conclusion

Rice leaf disease detection plays a vital role in improving agricultural productivity by enabling early disease identification, which is essential for reducing crop losses and ensuring food security. Our proposed system aims to provide a lightweight, efficient, and scalable solution for disease detection, especially in resource-constrained environments. By utilizing advanced deep learning techniques, our model effectively detects five common rice leaf diseases, demonstrating the potential for high accuracy and real-time disease management in agricultural practices. Our proposed solution significantly outperforms existing methods by achieving a high detection accuracy, with extensive validation confirming its robustness. This model can be deployed on low-cost hardware, making it accessible to farmers, particularly in rural and remote areas with limited resources. Through its real-time capabilities, the system offers immediate disease detection alerts, empowering farmers to take timely actions and reduce reliance on pesticide use, thereby promoting sustainable agricultural practices. In comparison to traditional models, such as CNNs, our approach based on EfficientNetV2 and Vision Transformer (ViT) shows superior generalization across diverse environmental conditions and improves disease detection accuracy. ViT, in particular, adapts well to both balanced and imbalanced datasets, capturing global context with its self-attention mechanisms, which enhances its ability to identify diseases with complex symptoms. While current results are promising, future research will focus on expanding the dataset to include a wider range of rice leaf diseases and incorporating multimodal data sources to improve model robustness. Additionally, optimizing the model for real-time applications will further enhance its practicality and scalability, addressing challenges related to computational complexity and model performance in resource-constrained environments. Overall, the proposed rice leaf disease detection system holds significant promise in advancing precision agriculture, supporting farmers in their efforts to mitigate disease outbreaks, and ultimately contributing to improved

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crop yield and food security.

Future Research

Future research for our rice leaf disease detection system will focus on several key areas to enhance its accuracy, scalability, and applicability in real-world agricultural settings.

Expansion to Additional Crop Diseases: Our current model targets five common rice leaf diseases, but expanding research to include additional crop diseases will increase its versatility and broader applicability. This will also involve exploring other agricultural crops and diseases that can benefit from similar diagnostic tools.

Integration of Multimodal Data: Future research will explore the integration of multimodal data sources, including weather data, soil conditions, and satellite imagery, to improve model performance and robustness. By incorporating such diverse data, the system will provide more comprehensive insights into disease management, considering regional and environmental factors.

Improvement in Dataset Diversity: A major challenge in disease detection is the diversity of symptoms across rice varieties and environmental conditions. Future studies will focus on collecting more diverse datasets from various regions, enhancing the model's ability to recognize symptoms in different environments and improve its generalization across different rice types.

Ensemble Learning and Hybrid Approaches: Building on the strengths of individual models like EfficientNetV2 and ViT, we plan to explore ensemble learning approaches. Combining multiple models can further boost disease detection accuracy and robustness. Hybrid systems may be explored to combine the strengths of CNNs and ViTs for better disease classification results.

Real-Time Applications and Optimization: As computational demands can be high for deep learning models, optimizing our current system for real-time applications will be a key research focus. This will involve refining the efficiency of the ViT model and other architectures, enabling deployment in resource-constrained environments like those found in rural agricultural settings.

Advanced Image Processing Techniques: To improve model precision, exploring advanced image processing techniques for better feature extraction will be crucial. These methods can help handle noisy, low-quality images or images with complex visual features, further enhancing detection capabilities.

Exploration of Transfer Learning and Fine-Tuning: Future work will involve exploring the full potential of transfer learning, especially in cases with limited data. Fine-tuning pre-trained models like ViT and EfficientNetV2 for specific rice disease detection tasks could improve the accuracy of disease classification, even with smaller or imbalanced datasets.

Collaborative Research and Farmer Community Involvement: Collaboration with farmer communities will be essential for real-world evaluation and refinement of the system. Gathering feedback from farmers about the system's usability and effectiveness will help refine the detection methods and ensure the tool is both practical and beneficial in field conditions. By addressing these areas, the future of rice disease detection systems can be enhanced, improving early disease detection, providing actionable insights to farmers, and ultimately contributing to sustainable agricultural practices and higher crop yields.

References

[1]. Rachman, Rahadian Kristiyanto, et al. "Enhanced Vision Transformer and Transfer Learning Approach to Improve Rice Disease Recognition." Journal of Computing Theories and Applications 1.4 (2024): 446-460.

[2]. Firnando, Fadel Muhamad, et al. "Analyzing InceptionV3 and InceptionResNetV2 with Data Augmentation for Rice Leaf Disease Classification." Journal of Future Artificial Intelligence and Technologies 1.1 (2024): 1-11.

[3]. Simhadri, Chinna Gopi, et al. "Deep learning for rice leaf disease detection: A systematic literature review on emerging trends, methodologies and techniques." Information Processing in Agriculture (2024).

[4]. Kulkarni, Priyanka, and Swaroopa Shastri. "Rice leaf diseases detection using machine learning." Journal of Scientific Research and Technology (2024): 17-22.

[5]. Trinh, Dong Cong, et al. "Alpha-EIOU-

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 01 January 2025
Page No: 31-51
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0006

YOLOv8: an improved algorithm for rice leaf disease detection." AgriEngineering 6.1 (2024): 302-317.
[6]. Bijoy, Mehedi Hasan, et al. "Towards Sustainable Agriculture: A Novel Approach for Rice Leaf Disease Detection Using dCNN and Enhanced Dataset." IEEE Access (2024).
[7]. Faqih, Rifqi Raenanda, Muhamad Irsan, and Muhammad Faris Fathoni. "Rice plant disease detection system using transfer learning with mobilenetv3large." Sinkron: jurnal dan penelitian teknik informatika 8.2 (2024): 805-812.
[8]. Setiawan, Rudi, and Hayatou Oumarou. "Classification of Rice Grain Varieties Using Ensemble Learning and Image Analysis Techniques." Indonesian Journal of Data and Science 5.1 (2024): 54-63.
[9]. Ritharson, P. Isaac, et al. "DeepRice: A deep learning and deep feature based classification of Rice leaf disease subtypes." Artificial Intelligence in Agriculture 11 (2024): 34-49.
[10]. Ahad, Md Taimur, et al. "Comparison of CNN-based deep learning architectures for rice diseases classification." Artificial Intelligence in Agriculture 9 (2023): 22-35.
[11]. Setiawan, Rudi, et al. "Rice Leaf Disease Classification with Machine Learning: An Approach Using Nu-SVM." Indonesian Journal of Data and Science 4.3 (2023): 136-144.
[12]. Tholkapiyan, M., et al. "Performance analysis of rice plant diseases identification and classification methodology." Wireless Personal Communications 130.2 (2023): 1317-1341.
[13]. Mustofa, Sumaya, et al. "A comprehensive review on Plant Leaf Disease detection using Deep learning." arXiv preprint arXiv:2308.14087 (2023).
[14]. V.K. Shrivastava and M.K. Pradhan, "Rice Plant Disease Classification Using Color Features: A Machine Learning Paradigm", J. Plant Pathol, vol. 103, pp. 17-26, 2020.
[15]. Bharanidharan, N., et al. "Multiclass Paddy Disease Detection Using Filter Based Feature Transformation Technique." IEEE Access (2023).
[16]. Acharya, Snehaprava, et al. "Performance comparison between svm and ls-svm for rice leaf disease detection." EAI Endorsed Transactions on Scalable Information Systems 10.6 (2023).
[17]. Arya, Akash, and P. K. Mishra. "A comprehensive review: advancements in pretrained and deep learning methods in the disease detection of rice plants." Journal of Artificial Intelligence and Capsule Networks 5.3 (2023): 246-267.
[18]. Mahadevan, K., A. Punitha, and J. Suresh. "A Novel Rice Plant Leaf Diseases Detection Using Deep Spectral Generative Adversarial Neural Network." International Journal of Cognitive Computing in Engineering (2024).
[19]. Bhaskar, Navaneeth, et al. "A Deep Learning Hybrid Approach for Automated Leaf Disease Identification in Paddy Crops." 2024 International Conference on Distributed Computing and Optimization Techniques (ICDCOT). IEEE, 2024.
[20]. Faqih, Rifqi Raenanda, Muhamad Irsan, and Muhammad Faris Fathoni. "Rice plant disease detection system using transfer learning with mobilenetv3large." Sinkron: jurnal dan penelitian teknik informatika 8.2 (2024): 805-812.
[21]. Deari, Sabri, and Sezer Ulukaya. "A hybrid multistage model based on YOLO and modified inception network for rice leaf disease analysis." Arabian Journal for Science and Engineering 49.5 (2024): 6715-6723.
[22]. Chen, Sishi, et al. "Early surveillance of rice bakanae disease using deep learning and hyperspectral imaging." aBIOTECH (2024): 1-17.
[23]. Mannepalli, Praveen Kumar, et al. "Diagnosis of bacterial leaf blight, leaf smut, and brown spot in rice leafs using VGG16." Procedia Computer Science 235 (2024): 193-200.
[24]. Sindhu, B. V. M., et al. "Paddy Leaf Disease Detection Using Ensemble Stacking." 2024 IEEE 9th International Conference for

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 01 January 2025
Page No: 31-51
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0006

Convergence in Technology (I2CT). IEEE, 2024.

[25]. Hossen, Sk Hapijul, et al. "Paddy Leaf Diseases Detection Using Otsu and Yen Thresholding with Deep Convolutional Neural Network." Internet of Things-Based Machine Learning in Healthcare. Chapman and Hall/CRC 126-146.

[26]. Ajay, Kommineni, et al. "Paddy Crop Disease Detection using LeNet and MobileNet Models." 2024 11th International Conference on Computing for Sustainable Global Development (INDIACom). IEEE, 2024.

[27]. Parasa, Gayatri, Mrs M. Arulselvi, and Shaik Razia. "Identification of Diseases in Paddy Crops Using CNN." (2024).

[28]. El-Shahat, Doaa, Ahmed Tolba, and Amit Krishan Kumar. "An Improved Deep Learning Model for Detecting Rice Diseases." Optimization in Agriculture 1 (2024): 1-10.

[29]. Lu, Yang, et al. "Image recognition of rice leaf diseases using atrous convolutional neural network and improved transfer learning algorithm." Multimedia Tools and Applications 83.5 (2024): 12799-12817.

[30]. Khalid, Zainab, et al. "A Deep Learning-Based Technique for Classification of Rice Leaf Disease Using Transfer Learning." Kurdish Studies 12.2 (2024): 5462-5478.