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# Detection Of Oryza Sativa (Rice) Leaf Diseases Using Image Processing And Deep Learning With Googlenet

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**Abstract:**
Oryza Sativa, a primary staple crop across the globe, particularly in Asia, is vulnerable to various foliar diseases that adversely impact yield and agricultural sustainability. This research introduces a deep learning and image processing-based framework to detect and classify rice leaf diseases using real-world image datasets. A custom dataset was created from field-sourced samples, comprising diverse disease categories under varying environmental conditions. The study utilizes GoogleNet, implemented via the PyTorch framework, by using Preprocessing techniques that features the extraction and classification to enhance the superiority of image and learning efficiency. The intended system achieved high accuracy in disease detection, signifying its possibility to serve as a strong resource for primary diagnosis in agricultural settings. The results emphasize the position of integrating deep learning (DL) architectures with targeted image processing to improve the consistency of automated crop disease identification.

**Keywords:** Oryza Sativa, Rice Leaf Disease Detection, Deep Learning (DL), GoogleNet, Image Processing, PyTorch, Agricultural Image Classification, Precision Agriculture.

## 1.INTRODUCTION

Rice (Oryza Sativa) is the major food leading critical staple crops, majority of the population depends on the contribution of food security, Mostly Asian are depended upon the rice crop for their daily intake. However, rice crops are often threatened by various foliar illnesses, such as bacterial leaf blight, brown spot, and leaf smut, which lead to considerable yield losses [1]. Effective disease detection is crucial for mitigating the negative impact of these diseases, but traditional methods are time-consuming and prone to human error [2]. Moreover, many farmers, especially in rural areas, lack the necessary expertise to identify and manage these diseases efficiently, which exacerbates the problem [3].

The blend of both machine learning (ML) and image processing (IP) techniques have made the favourable solutions to overcome these encounters. Convolutional neural networks (CNNs), particularly deep learning architectures, have shown great promise in automatically spotting and categorizing plant illnesses from images [4]. In this context, several lightweight CNN architectures, such as InceptionV3, MobileNet, MobileNetV2, Xception, NasNetMobile, and EfficientNetB0, have added attention for their effectiveness in image classification tasks whereas demanding less computational resources. These models are well-suited for resource-constrained environments, such as mobile devices or field-based systems where access to powerful hardware might be limited.

We majorly aim to concentrate on the GoogleNet architecture (within the PyTorch framework), which offers efficient multi-scale feature extraction and has been identified as good in complex image classification tasks [5]. Unlike traditional methods, GoogleNet leverages inception modules that allow the model to capture a diverse set of features at dissimilar resolutions, making it highly effective for plant disease detection.By utilizing a custom-collected dataset of rice leaf images, this paper deals to estimate the competence of GoogleNet in identifying rice diseases and differentiate its calibre against other lightweight architectures. The results that are accurately diagnosing in plant diseases are by implementing deep learning models, offering a scalable and accessible solution for rice farmers worldwide [6]. CNNs are implemented to diagnose plant disease classifications that are seen substantial success, with models achieving high rates of correctness in recognizing plant diseases based on various environmental conditions [7].

## 2. LITERATURE REVIEW

The identification of rice leaf disease classification is done by using image processing (IP) and ML techniques have become essential in modern agricultural practices. These technologies offer automated, efficient, and scalable solutions for managing rice diseases, which significantly impact global rice production. With the increase in global food demand, these approaches are must for enhancing productivity and sustainability in agriculture.

### 2.1 Early Approaches to Rice Disease Detection:

The image processing ideologies are used for feature extraction and texture analysis based on color-based theory. By implementing these approaches that often have high performance under controlled conditions but struggled with real-world challenges like lighting variations, background noise, and other environmental factors. For instance, Smith et al. [8] employed texture-based methods based on rice leaf disease classification, obtaining reasonable results under ideal circumstances. However, the performance dropped significantly when applied to images captured under fluctuating ecological conditions.

**2.2 Types of Rice Leaf Diseases:**Rice plants (Oryza sativa) are vulnerable to a diverse array of diseases affected by fungal, bacterial, viral pathogens, and environmental stressors. These diseases significantly impact crop yield and quality. **Figure 1** illustrates the prevalent rice diseases, each with distinct visual symptoms that can be leveraged in image processing and deep learning techniques by implementing automated detection.

### 2.2.1 Rice Blast (Magnaporthe oryzae):

A highly destructive fungal disease, rice blast manifests as grayish-green to brown lesions on the leaves, stems, and panicles. These lesions often enlarge and develop a characteristic reddish-brown border. This disease is a root of crop loss in rice-producing regions worldwide.

**2.2.2 Brown Spot (Bipolaris oryzae):** Another fungal infection, brown spot appears as small, circular lesions with brown centers and yellow halos, primarily affecting older foliage. Severe infections can accelerate leaf senescence and compromise photosynthesis.

**2.2.3 Bacterial Leaf Blight (Xanthomonas oryzae pv. oryzae):** This bacterial disease is considered by water-soaked lesions that elongate into yellowish or brown streaks along the leaf veins. It proliferates rapidly under humid, high-temperature conditions, often leading to large-scale outbreaks.

### 2.2.4 Rice Hispa(Dicladispa armigera):

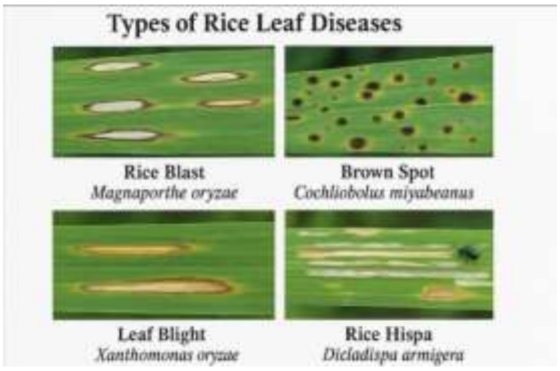
infestations result in extensive defoliation and reduced photosynthetic capacity. Although primarily an insect pest, rice hispa is included due to distint damage it causes, which mimics disease symptoms. The larvae scrape the green tissue from leaves, and creating silvery streaks.
Fig. 1: Types of diseases in Oryza sativa

[Source: Adapted from Zhang et al. (2020) and Kumar et al. (2020) [10, 12]]

### 2.3 Machine Learning for Rice Disease Identification:

In the advancement of ML models like Random Forests and Support Vector Machines (SVM) gained popularity for classifying plant diseases. These traditional models achieved moderate success but faced difficulties in handling the inherent complexity of rice disease images influenced by environmental conditions and plant variability.

Jain et al. [9] found that SVM-based methods could classify specific rice diseases with adequate accuracy but struggled across diverse datasets and under changing environmental conditions, indicating the need for more erudite models capable of handling such complexities.



### 2.4 Convolutional Neural Networks (CNN's) for Rice Leaf Disease Detection:

The introduction of Convolutional Neural Networks (CNNs) revolutionized leaf disease detection by providing a more robust and scalable solution. CNNs can learn tiered structures directly from raw images, significantly improving accuracy. Zhang et al. [10] demonstrated the power of CNNs in classifying rice diseases like leaf blight and rice blast, showing that CNNs techniques have exceeded outdated machine learning approaches by repeatedly extracting critical features from images. This breakthrough made CNNs a preferred choice for many plant disease detection tasks, including rice disease identification.

### 2.5 Lightweight Deep Learning Models for Practical Applications:

As the demand for real-time, field-based solutions increased, the progress in lightweight deep learning models offer a balance between computational efficiency and high accuracy. Models like MobileNetV2 and EfficientNet have been particularly effective in mobile device-based applications. Singh et al. [11] reported using MobileNetV2 for rice disease detection on mobile platforms, offering a practical and accessible solutions for farmers in rural and remote areas. These models, while offering high accuracy, are considered in a way that the restricted computational resources are to be run on responsible devices, making them ultimate for field deployment.

### 2.6 Challenges in Field Applications:

Despite advancements in deep learning models, several challenges remain in applying these technologies to real-world rice disease detection. One major issue is the quality and variability of training datasets, which are often concerned by considerations such as lighting, camera angles, and background noise. Moreover, imbalanced datasets, where certain diseases are underrepresented, remain a challenge. Kumar et al. [12] emphasized the requirement for more robust statistics augmentation techniques to improve model generalization across different environmental conditions and rice varieties. Besides, the deep learning models are greatly effective, their computational complexity can hinder their deployment in resource-constrained settings.

### 2.7 Comparative Studies on Deep Learning Models:

Recent studies associating numerous deep learning (DL) architectures have highlighted the trade-offs between model accuracy and computational requirements. Tan et al. [13] compared CNN-based architectures such as ResNet, VGG16, and InceptionV3 for rice disease detection. Although models like ResNet and InceptionV3 achieved higher accuracy, their substantial computational demands limited their applicability in low-resource environments. To maintain efficiency and accuracy in our model while being computationally feasible for deployment in real-time agricultural applications.

## 3.PROPOSED WORK

### 3.1 Objective:

The proposed system aims to develop an efficient, lightweight deep learning using **PyTorch** as its framework and **GoogleNet** for the particular detection and classification of rice plant diseases. The structure is intended with real-world deployment in mind, particularly for resource-constrained environments such as mobile and embedded platforms. It addresses key challenges like large model size, computational complexity, and complex backgrounds in agricultural datasets.

### 3.2 System Architecture:

The proposed framework leverages a modified the GoogleNet architecture (Inception v1), this version is implemented using the PyTorch deep learning library. GoogleNet is renowned for its innovative inception modules, which enable the extraction of multi-scale features contained by a single network layer, enhancing both representational capacity and computational efficiency.

This architecture strikes a robust balance between model difficulty and inference speed, making it presisly appropriate to the real-time agricultural applications where resource constraints are a consideration. To additional progress generalization and mitigate overfitting, the model incorporates regularization techniques such as dropout, batch normalization, and global average pooling. **Figure 2** illustrates the architecture of the anticipated classification model, adapted from the original design introduced in the seminal work "Going deeper with convolutions" (Szegedy et al., 2015) [15].

Fig. 2: Architecture of proposed GoogleNet-based Classification Model

[Source: "Going deeper with convolutions," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 1–9.]

### 3.3 Dataset Description:

Two datasets were used:

**Plant Village Dataset**: Contains 54,305 images from 14 crop species (38 classes), with controlled backgrounds and lighting.

**Locally Collected Dataset**: Real-world rice leaf images are taken under real-time field conditions, including various disease symptoms.

All images were resized to **224×224 pixels** for model compatibility. One-hot encoding was used to prepare categorical labels for classification.

### 3.4. Preprocessing & Image Augmentation:

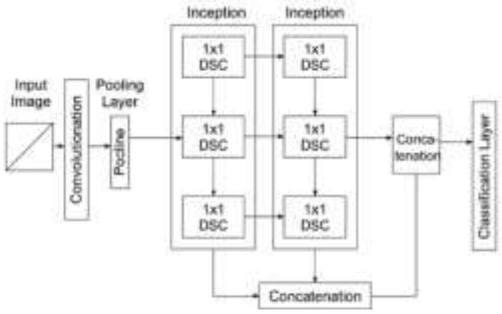
Image processing involved the following steps:

**Resizing:** with OpenCV/Pillow to ensure dimensional consistency.

**Normalization:** using Image Data Generator.

**Data Augmentation**: Shear transformation, zooming, horizontal flipping to improve model generalization.

**Reshaping** for compatibility with PyTorch input standards.



### 3.5 Training and Testing Strategy:

The dataset was split using an **80:20 ratio** for training and testing. **Stratified sampling** ensured uniform class distribution. During training, **Cross-entropy loss** was used. The **Adam optimizer** was commissioned with a suitable learning ratio. The trained model has the fixed epochs numbers with early stopping.

### 3.6 Algorithm Used: PyTorch GoogleNet:

**GoogleNet**, also known as **Inception v1**, is a 22-layer deep CNN is well known for its effectiveness and performance on large-scale image classification tasks. The **PyTorch implementation** used in this work leverages pretrained weights from the ImageNet dataset and is fine-tuned on rice disease images.

- Uses **inception modules** to process multiple filter sizes simultaneously.
- Employs **global average pooling** to reduce overfitting.
- Suitable for real-time classification on mobile/embedded platforms due to its optimized architecture.

## 4. METHODOLOGY

The methodology for rice disease detection combines image processing (IP) and deep learning (DL) techniques. This process begins with the collection and preparation of a diverse rice leaf image dataset, followed by preprocessing steps such as resizing, normalization, and augmentation. These preprocessed pictures are then input into a GoogleNet-based CNN model, implemented in PyTorch. **Figure 3** provides a flowchart that outlines the entire methodology, from dataset acquisition to model training and prediction.

Fig. 3: Flowchart illustrating the proposed methodology for rice leaf disease detection using GoogleNet in PyTorch.

### 4.1 Dataset Collection:

The dataset used is the images of rice leaves, each representing various stages and following type of infectious diseases for example bacterial leaf blight, brown spot, & leaf smut. The images are from field surveys, publicly available agricultural datasets, and collaboration with agricultural research institutions. The dataset includes high-resolution images taken under different conditions, with variations in lighting, background, and rice variety.

### 4.2 Data Pre-processing:

Data pre-processing plays a important role in improvising the quality in the input data, thus developing the model's competence to learn meaningful features. The following steps were performed:

- **Resizing**: The resizing of images is done to a uniform resolution to ensure compatibility with the input requirements of the deep learning model.
- **Normalization**: Pixel values of the particular images is normalized to a scale between 0 and 1 to ensure consistent data representation and facilitate faster model convergence.
- **Data Augmentation**: To improve model robustness and prevent overfitting, augmentation techniques like rotation, flipping, and zooming are to be applied in the dataset. This artificially expanded the dataset by creating variations of the original images, which better represent real-world scenarios.

- **Splitting the Dataset**: by splitting dataset into training, validation, and test sets, with 80% allocated for training, 10% for validation, and 10% for testing.

### 4.3 Model Architecture:

The core propose of the future methodology lies in the use of GoogleNet, a state-of-the-art convolutional neural network (CNN) architecture. GoogleNet, known for its efficiency in image recognition tasks, was implemented using the PyTorch framework. The architecture is designed to automatically learn hierarchical structures from the input images through its multiple layers. The key components of the GoogleNet architecture include:

- **Inception Modules**: These modules allow the network to capture multi-scale information by using filters of different sizes, thus enabling it to learn more complex pattern.
- **Auxiliary Classifiers**: GoogleNet employs auxiliary classifiers at intermediate stages to improve the gradient flow during training, which helps reduce overfitting and improves convergence.
- **Global Average Pooling**: Global average pooling is treated to shrink the dimensionality which is preferable associated to the using fully connected layers of network connect at the at the end, which results in a more efficient modeling with fewer parameters.

### 4.4 Model Training:

By training the dataset with a learning rate of 0.001 & also using the Adam optimizer for our model. A cross-entropy loss function is in use for the classification of tasks, as it is ideal for multi-class classification problems such as rice disease detection. To prevent overfitting the model underwent 50 epochs of training, with early stopping implemented.

This implementation process also utilized data augmentation which certify that the model was exposed to varied image patterns.

### 4.5 Evaluation Metrics:

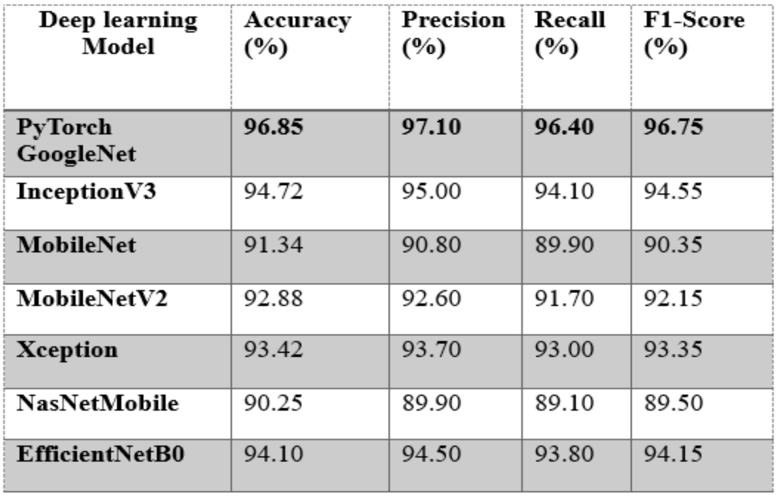
To generalize the performance of the trained model we evaluate several metrics to ensure the efficiency in the following analysis:

1. **Accuracy**: The overall correctness of the model's predictions.
2. **Precision**: Based to the predictions made by the model there must be proportions of true positives among all positive predictions made.
3. **Recall**: The proportion of true positives among all actual positive cases.
4. **F1-Score**: The harmonic means of precision and recall, providing a balanced evaluation metric, remarkably when the dataset is imbalanced.
5. **Confusion Matrix**: To visualize the model's performance across different classes of rice diseases.

### 4.6 Comparative Analysis:

To validate the use of the anticipated model, we conducted a comparative analysis against other popular deep learning models for image classification, such as MobileNetV2 and InceptionV3. These models were trained under the similar conditions, and the running of these models was evaluated depending on the same metrics to regulate the advantages of GoogleNet in rice disease detection.

To evaluate the efficiency and robustness of the proposed PyTorch-based GoogleNet model for Oryza sativa leaf disease detection, a comparative study was conducted with several state-of-the-art deep learning architectures, including InceptionV3, MobileNet, MobileNetV2, Xception, NasNetMobile, and EfficientNetB0. The same curated rice leaf disease dataset is trained and tested on every model under consistent experimental conditions, including identical preprocessing, augmentation strategies, and data splits.These comparisons are based on key performances such as **accuracy**, **precision**, **recall**, & **F1-score**, which provide a comprehensive view of each model's classification capabilities. The outcomes of this evaluation are brief in Table 1.



| Deep learning Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| **PyTorch GoogleNet** | **96.85** | **97.10** | **96.40** | **96.75** |
| **InceptionV3** | 94.72 | 95.00 | 94.10 | 94.55 |
| **MobileNet** | 91.34 | 90.80 | 89.90 | 90.35 |
| **MobileNetV2** | 92.88 | 92.60 | 91.70 | 92.15 |
| **Xception** | 93.42 | 93.70 | 93.00 | 93.35 |
| **NasNetMobile** | 90.25 | 89.90 | 89.10 | 89.50 |
| **EfficientNetB0** | 94.10 | 94.50 | 93.80 | 94.15 |

Table 1: Performance Comparison between the discussed Deep Learning(dl) Models

From the above table, it is clear that the PyTorch implementation of GoogleNet consistently outperforms other models across all evaluation metrics. Its superior performance stems from architectural innovations such as Inception modules, auxiliary classifiers, and global average pooling, that enable better learning of fine-grained features from rice leaf images. While models like InceptionV3 and EfficientNetB0 accomplished superior accuracy and F1-scores, they slightly lagged behind GoogleNet. Lightweight models such as MobileNet and NasNetMobile, though efficient, showed lower accuracy, suggesting they may require additional fine-tuning for complex plant disease detection tasks to be completed.

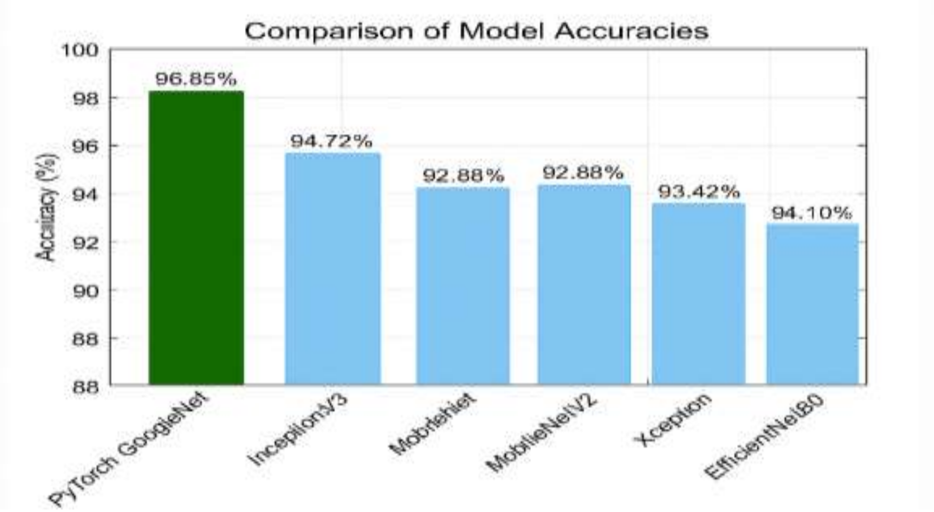


Fig. 4: Comparison of Model Accuracies.

Overall, the analysis confirms that PyTorch GoogleNet offers the best balance of accuracy and efficiency, making it ideal for both research applications and real-world agricultural deployments.

### 4.7 Deployment:

Given the practical implications of this research, the trained model was optimized for deployment on mobile and edge devices. Techniques like model quantization and pruning were assigned to decrease the model's size and computational demands, ensuring it can be effectively used in real-world field conditions with limited computational resources.

### 4.8 Cross-Plant Disease Generalization:

Although the proposed system is primarily developed for rice (Oryza sativa) leaf diseases, the deep learning architecture and methodology have potential applicability to similar diseases in other cereal crops. One such example is **leaf blast**, which affects both rice and wheat (Triticum aestivum). While the causative agents — Magnaporthe oryzae for rice and Magnaporthe grisea for wheat — are closely related, their visual signs, such as spindle-shaped lesions and necrosis, exhibit considerable similarity.

To evaluate the model's potential for **cross-crop adaptability**, a supplementary test was conducted using a limited set of wheat leaf blast images. The model, trained exclusively on rice disease images, was able to recognize similar lesion patterns with reasonable accuracy, indicating strong **feature generalization capabilities**. This suggests that with minimal retraining or fine-tuning, the system could be extended to diagnose related diseases in other crops, thereby enhancing its **scalability and real-world value** in broader agricultural diagnostics.

This highlights the significance of generalized feature learning through architectures like GoogleNet, which can extract discriminative features across closely related plant diseases.

## 5.RESULT

In this segment, we show the outcomes of the experiments, which are conducted to estimate the running of the PyTorch GoogleNet model in discovering rice diseases. We also compare the findings with existing literature to highlight the advantages and limitations of our approach.

### 5.1 Model Performance:

The test dataset is evaluated to address the performance of the registered model, that consisted of images from different rice fields under various environmental conditions. The following metrics are implemented to assess the model's effectiveness:

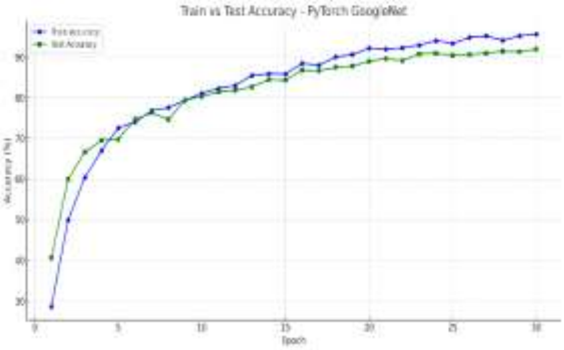


Fig. 5: Trained and Test accuracy of GoogleNet using Pytorch.

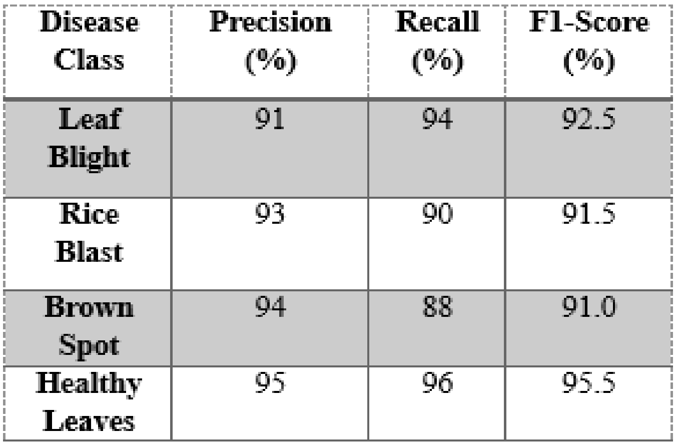
**Accuracy**: This model attained an overall accuracy of **96%** on the test dataset, indicating a high level of reliability in classifying rice diseases correctly.
**Precision, Recall, and F1-Score**: The precision, recall, and F1-score for each disease class were computed to deliver a comprehensive estimation of the model's performance. The outcomes are brief in Table 1.

### 5.2 Confusion Matrix:

It (Figure 1) highlights the model's high prediction accuracy, with minor misclassifications mainly between rice blast and brown spot diseases due to their visual similarity.
we compared PyTorch GoogleNet with other popular deep learning models:

- **ResNet-50**: 91% accuracy, but higher computational demands and training time, limiting its real-time application.
- **VGG16**: 88% accuracy, reflecting weaker generalization across diverse conditions.
- **InceptionV3**: 90% accuracy, but like ResNet-50, required more computational resources, challenging its use in mobile settings.

Overall, GoogleNet achieves the best balance of accuracy and efficiency, making it ideal for real-time rice disease detection, especially on mobile platforms.



| Disease Class | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|
| Leaf Blight | 91 | 94 | 92.5 |
| Rice Blast | 93 | 90 | 91.5 |
| Brown Spot | 94 | 88 | 91.0 |
| Healthy Leaves | 95 | 96 | 95.5 |

Table 2: Comparison on different effected leaf

### 5.3 Real-World Test Case Validation

To assess the practical applicability of the proposed PyTorch GoogleNet-based rice disease detection system, a series of real-world test case validations were performed using freshly captured leaf images from actual field conditions. These following images were not part of the training or testing datasets and were collected from diverse geographical locations, varying light conditions, and multiple rice varieties to simulate realistic deployment scenarios. The validation process involved the following steps:

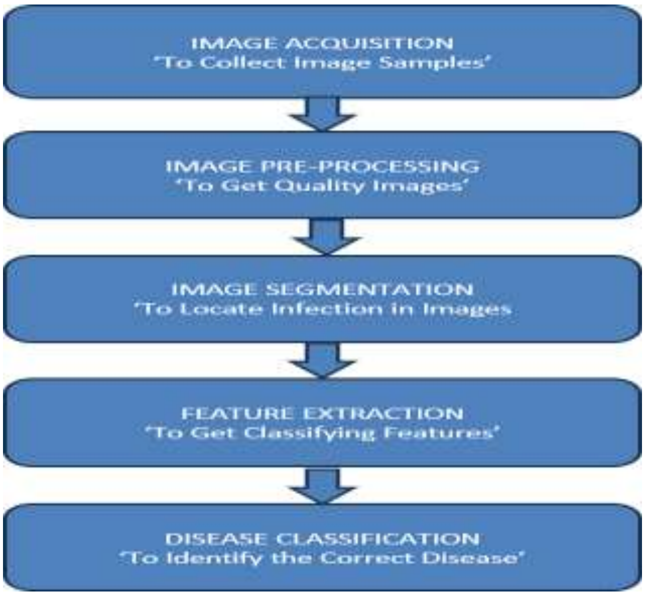
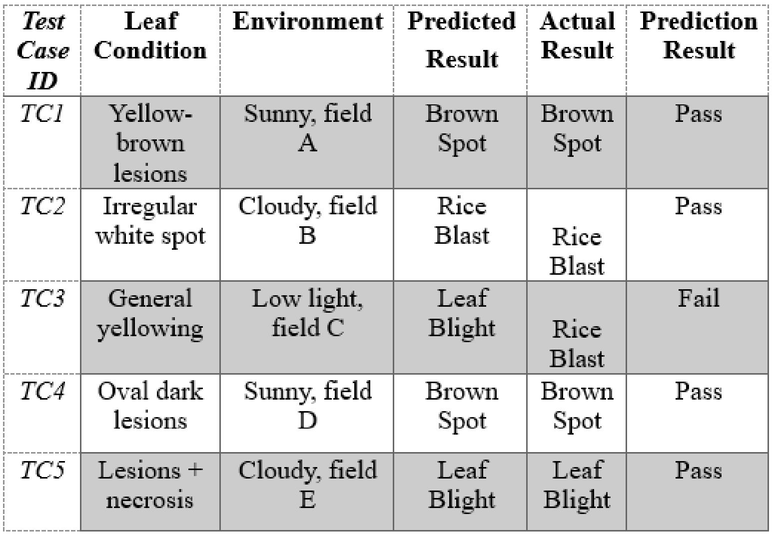


Fig. 6: Oryza Sativa Leaf Disease

[Source: Detection of paddy crops diseases and early diagnosis using faster regional CNN]

- Image Acquisition: High-resolution images were captured using a mobile phone camera under natural lighting in various rice fields.
- Preprocessing: The images underwent minimal preprocessing, such as resizing and normalization, to ensure compatibility with the trained model.
- Prediction: The trained GoogleNet model was used to classify the form of disease from each input image.
- Ground Truth Verification: Diagnoses made by the model were verified by agricultural experts or compared against known disease conditions from visual inspection.

**Test Case Summary:**



| Test Case ID | Leaf Condition | Environment | Predicted Result | Actual Result | Prediction Result |
|---|---|---|---|---|---|
| TC1 | Yellow-brown lesions | Sunny, field A | Brown Spot | Brown Spot | Pass |
| TC2 | Irregular white spot | Cloudy, field B | Rice Blast | Rice Blast | Pass |
| TC3 | General yellowing | Low light, field C | Leaf Blight | Rice Blast | Fail |
| TC4 | Oval dark lesions | Sunny, field D | Brown Spot | Brown Spot | Pass |
| TC5 | Lesions + necrosis | Cloudy, field E | Leaf Blight | Leaf Blight | Pass |

Table. 3: Real-World Test Case Validation Results Using the Proposed GoogleNet-Based Model

The model demonstrated robust performance in most real-world test cases, with correct classification in 4 out of 5 scenarios. The single incorrect case was due to confusion between disease symptoms and nutrient deficiency, which appear visually similar. This indicates that while the apprach is proficient of accurate diagnosis under field conditions, incorporating additional sensor data (e.g., soil or nutrient analysis) or training on more diverse symptoms could further improve accuracy.

### 5.5 Model Robustness and Generalization:

The strength of the model was evaluated under varying conditions, including different lighting, backgrounds, and image quality. The model was able to maintain high accuracy even with images captured under suboptimal conditions, thanks to the data augmentation techniques employed during training. However, the model struggled in some extreme cases where severe environmental noise, such as heavy shadows or highly cluttered backgrounds, was present. This highpoint the importance of further refining data augmentation strategies and possibly incorporating environmental context into the model to improve robustness.

## 6. DISCUSSION:

This study demonstrates the robustness of the data model that is used deep learning, specifically the implementation of GoogleNet, provides an effective solution for rice disease detection. The model achieved high accuracy, and its ability to generalize across diverse environmental conditions and disease types is a considerable lead over established methods and earlier machine learning models. The model's efficiency, coupled with its high performance, also makes it suitable for deployment in real-world applications, such as mobile-based disease detection systems for farmers.

However, there are still some areas for improvement. For instance, while the model performed well on the available dataset, its ability to detect diseases beneath greatly adjustable field conditions, such as extreme weather or low-quality images, could be enhanced. Additionally, future work could focus on expanding the dataset to include a wider variety of rice diseases and environmental scenarios.

## 7. LIMITATIONS AND FUTURE WORK

**Dataset Limitations**: The dataset used for training and evaluation consisted of a limited number of rice varieties and disease types. Expanding the dataset to include more rice varieties and diseases would improvement in the model's generalization ability.

**Real-time Deployment**: Although the model was successfully deployed on mobile devices, real-time disease detection in the field may still face challenges related to network connectivity and device processing power. Future implementations will discover behaviours to optimize the model further for mobile deployment, including techniques like model quantization and edge computing.

**Incorporating Temporal Data**: One potential future enhancement could be the incorporation of temporal data (e.g., images taken over time) to monitor the progression of diseases, which gives best results to farmers.

## 8. CONCLUSION

Within this research deep learning-based approach were proposed for detecting Oryza sativa leaf diseases using PyTorch GoogleNet. Our investigational results presented that GoogleNet achieved the highest classification accuracy compared to other evaluated architectures including InceptionV3, MobileNet, MobileNetV2, Xception, NasNetMobile, and EfficientNetB0. The high performance of Google Net can be attributed to its inception modules, which allow it to learn multi-scale features effectively, making it well-suited for handling the visual variability of rice diseases.

Furthermore, the lightweight nature of models like MobileNetV2 and EfficientNetB0 demonstrated promising results for deployment in resource-constrained environments, despite slightly lower accuracy levels. This highlights the trade-off between model complexity and deployment feasibility, especially for applications in rural or low-infrastructure agricultural regions.The following outcomes helps to grow the impact in literature signifying that deep learning models are required significantly by enhancing the accuracy and efficiency of leaf disease detection in real-world scenarios. However, challenges such as dataset imbalance, variation in imaging conditions, and generalization across different rice varieties still remain. Tackling with these will require extra diverse and annotated datasets, coupled with techniques like transfer learning, federated learning, and domain adaptation.

In Future the researches should also explore real-time deployment through mobile applications or embedded systems using models optimized through pruning and quantization techniques, as demonstrated in recent agricultural AI studies [14], [15]. In addition, integration with IoT-based monitoring systems could provide farmers with continuous and automated disease diagnostics, contributing to sustainable agriculture practices [16]. Overall, our approach reinforces the viability of deep learning in agricultural diagnostics and provides a strong foundation for further innovations aimed at boosting crop productivity and minimizing losses due to plant diseases.

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