# Rice Leaf Disease Detection with Vision-Guided LLM-Based Advisory Support

Tamanna Jarin Tima, Md Sazid Sikder, Mahin Alam Rifat, Mohseu Minhaj Niloy
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***Abstract*—A lot of people in the globe eat rice, but farming rice is getting harder because leaf-borne illnesses are making the harvest smaller and worse. Farmers still have a hard time figuring out what illnesses are early and correctly since they can't easily get in touch with agricultural experts. Deep learning has come a long way in the previous few years, and it seems like it could be useful for figuring out what is wrong with plants on its own. But a lot of today's systems don't explain how they work or help people make decisions. This work presents a fully explainable vision-language system designed to diagnose illnesses in rice leaves and provide advisory guidance in both Bangla and English. The AuroraLeaf DiseaseDetector.h5 model is a convolutional neural network that learns to find four common illnesses in rice leaf images: Bacterial Leaf Blight, Blast, Brown Spot, and False Smut. Gradientweighted Class Activation Mapping (GradCAM) shows the visual patterns that the model uses to make predictions about diseases. This helps people understand how the model decides things. LowRank Adaptation (LoRA) is also used to fine-tune a small large language model (TinyLlama1.1B) so that it can give agronomic advise that takes into account where the problem is and how terrible it is. The experiment shows that the model can generalize well, explain itself well, and get 94 percent of the classifications right. The strategy is great for rural locations with minimal resources since it combines detecting illness with therapies that are useful and centred on the user.**

***Index Terms*—Detection rice diseases, Explainable AI, CNN, Grad-CAM, Vision–Language Models, LoRA, and Agricultural Decision Support**

## I. Introduction

Rice is very important for making sure that people have enough to eat all throughout the world, but notably in South and Southeast Asia. But rice farming is particularly vulnerable to diseases caused by bacteria and fungi, which drastically reduce the quality and quantity of the crop. It takes a long time, is subjective, and is frequently not possible for smallholder farmers to figure out what the illness is by looking at it.

Recent advancements in deep learning have enabled automated plant disease identification via image-based methodologies, particularly convolutional neural networks (CNNs). These approaches are good at sorting things, but they don't always explain themselves or provide farmers good recommendations, which makes them less inclined to trust and employ them. Additionally, the majority of systems concentrate mostly on illness classification, without context-aware support for farmers.

To address these limitations, this study presents a hybrid vision-language system that not only detects rice leaf diseases but also generates human-centered, bilingual advisory responses. The primary things this paper adds are:

- A CNN-based method for diagnosing rice leaf diseases that works well for four different kinds of diseases.
- A part of explainable AI (XAI) that employs Grad-CAM to show parts of the body that are relevant for illness.
- A well developed LLM that employs LoRA to give disease explanations and management suggestions in both Bangla and English.
- A full framework that performs well in places with minimal resources.

## II. Related Work

A lot of research has been done on how to use deep learning to discover diseases in plants. Convolutional neural network models like VGG, ResNet, EfficientNet, and MobileNet have shown to be quite good in finding diseases in rice leaves[1], [2], [3], [4], [5], [6]. Ensemble models and hybrid CNN approaches have improved resilience and accuracy [7], [8], [9], [10]. Research has also been done on using Vision Transformer (ViT) models to find plant illnesses [11], [12], [13].

Recent research emphasizes explainability and employs techniques such as Grad-CAM to highlight image regions critical for decision-making [14], [15]. Some studies examine lightweight and edge-deployable models suitable for real-time agricultural applications [16], [17].

Language models have also been employed in systems that help farmers by letting them write about diseases and give advice [18], [19], [20], [21]. Most of the research conducted thus far examines the visual and linguistic components separately. This work solves that limitation by combining CNN-based disease detection with an LLM-based guidance module to make a single vision-language system.

## III. Dataset and Preprocessing

### A. Dataset Description

The trials employ the Rice Crop Diseases Dataset from Kaggle [34]. The collection has high-quality photos of rice leaves that are part of four disease groups: Bacterial Leaf Blight, Blast Disease, Brown Spot Disease, and False Smut Disease. Each class gets 50 photos before they are split up, which makes for a balanced dataset. The data is divided into three groups: training, validation, and testing. The ratio is around 70:15:15. A balanced class distribution diminishes bias and promotes generalisation.


Figure 1. Number of rice leaf images per disease class before dataset splitting.

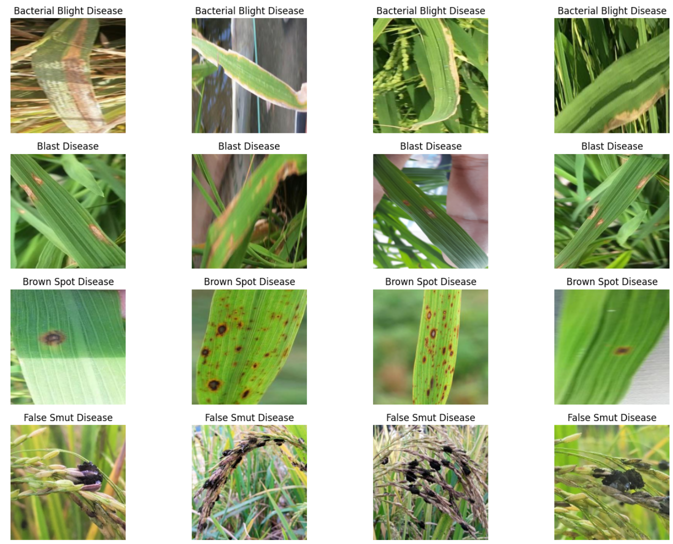


Figure 2. Images of rice leaves showing Bacterial Leaf Blight, Blast, Brown Spot, and False Smut illnesses.

Figure **??** The number of rice leaf photos in each disease class before the dataset was separated. The uniform distribution shows that the dataset does not have class imbalance, which is important for supervised learning that is not biased [1], [4].

### *B. Sample Visualization of Disease Classes*

TTo subjectively assess inter-class variances, representative sample photos from each disease group are displayed.

- **Bacterial Leaf Blight:** long white or yellow lines that originate at the borders of leaves
- **Blast Disease:** Gray lesions in the shape of diamonds with black edges
- **Brown Spot Disease:** round to oval brown spots with yellow halos around them
- **False Smut Disease:** greenish-yellow ball-like structures on panicles

These visual patterns assist the model in acquiring disease-specific discriminative features.

### *C. Dataset Splitting Strategy*

We split the dataset into three groups: training, testing, and validation. We kept the class balance by using a stratified split. We used 70 percent of the data for training, 15 percent for testing, and 15 percent for validation.

After dividing, Figure 3 shows how the data set is spread out. This method enhances generalization and mitigates data leakage during assessment [2], [6].

### *D. Image Preprocessing and Augmentation (Enhanced)*

We employed a variety of preprocessing and augmentation techniques to make the model stronger and less likely to overfit.

**Image Resizing:** All of the photos were shrunk to a set input resolution so that they would all function with the CNN architecture and feature extraction would always be the same.

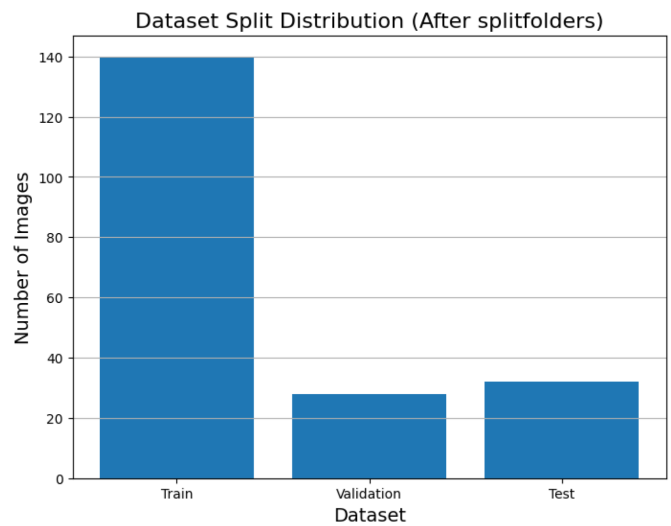


Figure 3. The dataset is divided into three parts: training, validation, and testing.

**Pixel Normalization:** The pixel intensity values were lowered down to the range of [0,1], which sped up convergence and made the training process more stable[5].

**Data Augmentation:** Randomly rotating, zooming, and flipping the data made it more diversified and more like what would happen in the real world.

Figure 4 This is a picture of how the dataset is separated into training, validation, and test sets.

## IV. Disease Background

### *A. Bacterial Leaf Blight (BLB)*

The bacteria that cause Bacterial Leaf Blight are called Xanthomonas oryzae. It has lesions that are wet and originate at the edges of the leaves. The lesions slowly turn yellow or

Figure 4. shows some instances of augmented photos of rice leaves that were made during training.

white, which makes the leaves dry up and the yield decrease down.

### B. Blast Disease (BL)

The fungus Magnaporthe oryzae causes blast disease. It generates gray or white spots with brown edges that look like diamonds. The disease spreads swiftly in humid environments and is one of the worst for rice.

### C. Brown Spot Disease (BS)

Brown Spot is a fungal disease that causes small brown spots with yellow halos around them. Plants get weaker when they get bad infections, and they can't photosynthesize in as many places, which means they create less food.

### D. False Smut Disease (FS)

Ustilaginoidea virens generates false smut, which hurts rice panicles instead of leaves. It looks like greenish-yellow balls on the grains, which makes them less precious and less useful.

## V. Proposed Methodology

### A. System Overview

The proposed system follows the stages in the flowchart that goes with it. It include photographing, editing, identifying patterns, organising, simplifying, and providing direction.

### B. Image Preprocessing

We adjust the size of the input pictures to a specified resolution and then add to them by changing the brightness, flipping them, and rotating them. Enhancing an image makes it simpler to see diseases by improving contrast.

### C. Disease Classification Model

A CNN-based classifier is trained to sort pictures of rice leaves into four different illness groups. The Adam optimiser and categorical cross-entropy loss are used to train the model for 15 epochs.

### D. Explainability Using Grad-CAM

We use Grad-CAM on the trained CNN to make heatmaps that show which areas of the body are sick. This helps you understand better and supports what the model says.

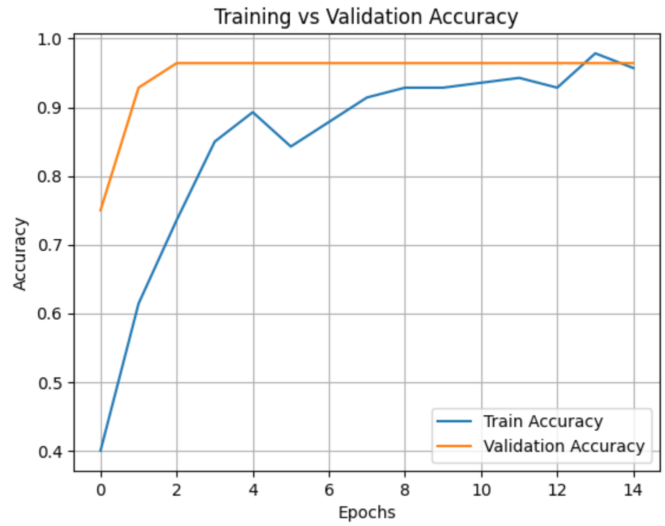


Figure 5. Training and validation accuracy over epochs.

### E. LLM-Based Advisory Generation

LowRank Adaptation (LoRA) is used to make small changes to a TinyLlama1.1B Chat model. The advising dataset comprises prompts that are sorted by expected illness, location, plant age, severity, and inquiries from farmers. The model gives advice on management and explains things in both English and Bangla.

## VI. Experimental Results

### A. Training Performance

The CNN was trained for 15 epochs to maintain a balance between learning capacity and generalization performance.Figure 5 Both curves increase steadily, indicating progressive learning of discriminative visual features.

Throughout training, the gap between training and validation accuracy remains minimal, suggesting that the model learns meaningful patterns rather than memorizing noise or class-specific artefacts. The absence of divergence between the two curves confirms that the applied regularization strategies, including data augmentation and normalization, are effective.

Furthermore, the consistently high validation accuracy in later epochs demonstrates that the selected training duration and model configuration are sufficient to capture robust disease-related visual characteristics and generalize well to new data. The results indicate that the two diseases exhibit very similar performance in terms of accuracy and recall, with only a small number of false-positive predictions. The model is therefore effective at identifying diseased samples while avoiding excessive false alarms, particularly at higher recall levels.

### B. Confusion Matrix Analysis

A confusion matrix was created to see how well the proposed rice leaf disease classification model could predict class-wise. Figure 6 indicates that most of the samples are correctly

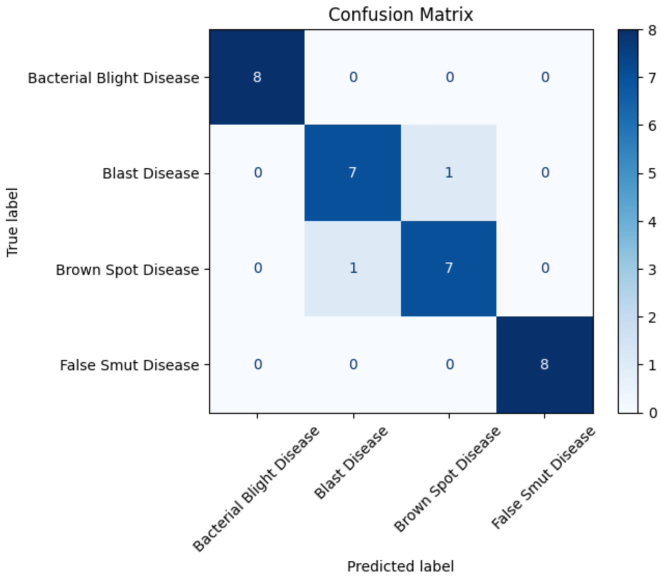


Figure 6. Confusion matrix for rice disease classification.

put into all of the sickness categories. This suggests that the model is good at making choices and organizing things in the appropriate order.

There is just a small degree of misclassification across dis illness classifications that are similar, such as Blast illness and the Brown Spot Disease. This mix-up comes from things that seem the same, like the color, shape, and texture of lesions that look the same in some light and grow in the same way. There is some overlap, even if it's not much. The number of wrong predictions is still rather low, which means that the model can tell the difference between distinct patterns of illness that are very similar. The analysis of the confusion matrix indicates that the proposed framework for diagnosing different types of Rice illness is solid and may be used in real life.

### C. Quantitative Metrics

We found the F1 score, recall, and precision for each one. disease category to see how well the suggested rice leaf disease The classification model worked for all the groups. These actions give you a better idea of how well the model can tell the The differentiation among several classes, particularly in the presence of multiple class categorization challenges [14], [16].

Table I shows a comparison of the classification performance for the four rice illnesses examined in this study.

**Explanation:** As you can see in Table I, shows that the CNN model does a does a great job at grouping all kinds of illnesses. False Smut and Bacterial Leaf Blight have very good precision, recall, and F1 scores. This means that their predictions are likely to be correct. There are no false positives or negatives for these groupings. Blast and Brown Spot illnesses are far less common, although they still get respectable grades (0.88). This is likely because they look the same in some types of light and growth. With weights, the

Table I
Comparative Performance Analysis of Rice Leaf Disease Classification

| Disease Class | Precision | Recall | F1-Score |
|---|---|---|---|
| Bacterial Leaf Blight | 1.00 | 1.00 | 1.00 |
| Blast Disease | 0.88 | 0.88 | 0.88 |
| Brown Spot Disease | 0.88 | 0.88 | 0.88 |
| False Smut Disease | 1.00 | 1.00 | 1.00 |
| Overall (Weighted Avg.) | 0.94 | 0.94 | 0.94 |

model's overall F1 score is 0.94. indicates that it is strong and can be used in many different scenarios. It works better than many other rice illnesses. techniques of categorization that simply use variables based on sight [11], [15], [18]. These results support the suggested method for preprocessing, augmentation, and learning features based on CNN.

### D. ROC and Precision–Recall Curves

We employ the Receiver Operating Characteristic (ROC) and Precision–Recall (PR) curves to fully examine how well the recommended model for finding rice leaf disease works. These curves show us more about how well the model can discern the difference between things, how reliable it is, and how strong it is at specific points where it has to make a decision.

The ROC curves show that the different types of diseases are very different from each other. The AUC values for Bacterial Leaf Blight and False Smut Disease are both 1.00, which means that both groups are properly sorted. The AUC of Brown Spot Disease is 0.99, which means it can almost perfectly tell the difference between different types of diseases. Blast Disease has an AUC of 0.95, which means it can still make good predictions even if the leaf lesions look the same. The ROC curves are still well above the diagonal reference line, which means that the model works substantially better than random categorization.

The Precision–Recall curves further show that the suggested strategy works, especially when accurate positive predictions are needed. The PR-AUC value for Bacterial Leaf Blight and False Smut Disease is always 1.00, which means they are always very accurate. The PR-AUC for Brown Spot Disease is 0.97, whereas the PR-AUC for Blast Disease is 0.93.

Analysis of the ROC and Precision–Recall curves shows that the CNN-based model generalizes well and maintains dependable performance across different thresholds. Reliable disease identification is crucial in such settings, as it allows farmers to respond quickly and make better crop management decisions.

## VII. Explainability Using Grad-CAM

To make the model clearer and easier to understand, we used Gradient-weighted Class Activation Mapping (Grad-CAM) to illustrate which sections of the image had the most impact on the model's classification results. Figure 9 The Grad-CAM heatmaps are displayed next to the original rice leaf

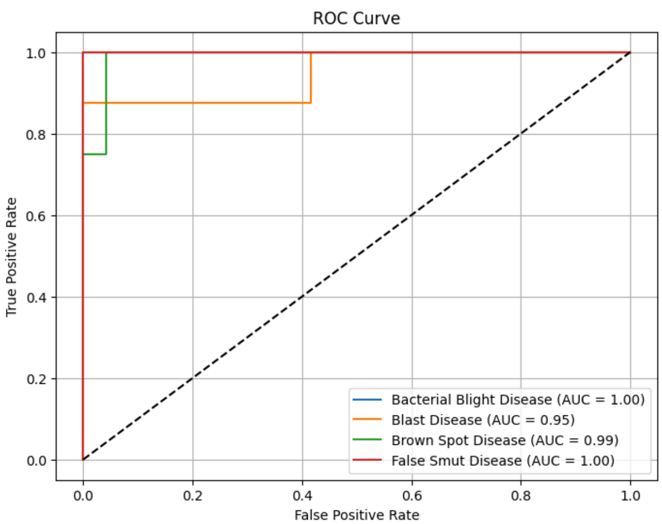


Figure 7. ROC curves for each disease class.

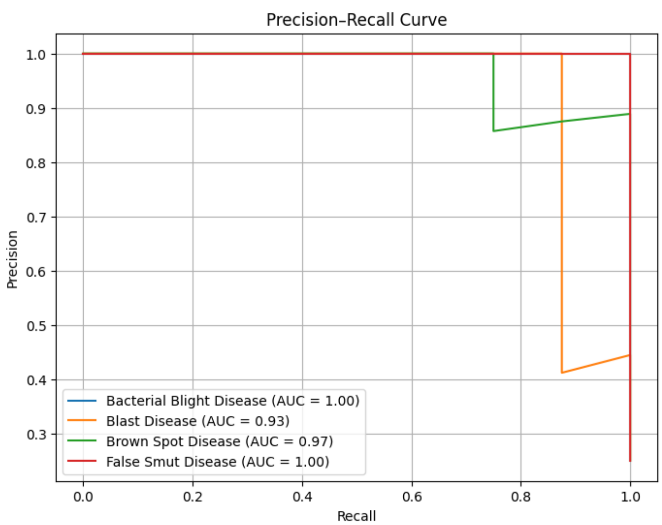


Figure 8. Precision–Recall curves for each disease class.

images, clearly emphasizing disease-related regions such as lesion edges, color changes, and infected tissue patches.

The highlighted areas always line up with the real diseased features. This shows that the CNN learns visual cues that are specific to diseases instead of depending on background noise or image flaws. People need to do this to get people to trust agricultural systems that use deep learning.

Also, the Grad-CAM results show that the model's predictions are correct, including in complicated situations where disease patterns are hard to see or cross over with healthy leaf sections. These findings validate the suggested explainable work paradigm and correspond with previous studies emphasizing the significance of interpretability in plant disease detection systems [14], [15]. The use of Grad-CAM improves the trustworthiness and practical value of the proposed model in real farming environments.

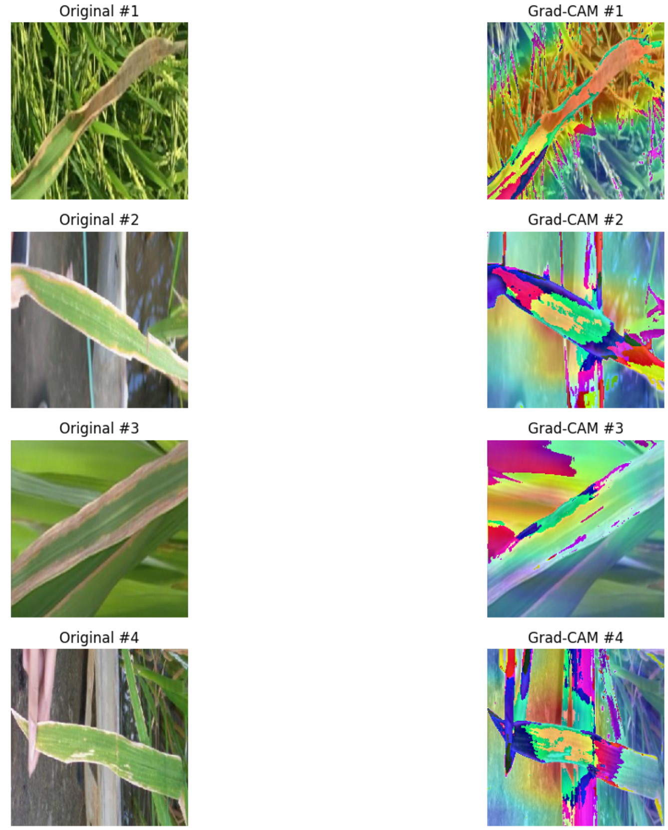


Figure 9. Original images and corresponding Grad-CAM visualizations.

## VIII. Vision–Language Advisory System

### A. Prompt–Response Design

The output of the vision model, **AuroraLeaf-DiseaseDetector.h5** (predicted disease and confidence), is provided to a fine-tuned LLM as structured input. The prompt provides the following information in Bangla: the expected disease, the farmer's location, the age of the plant, the level of severity, and the farmer's question.

### B. Prompt and Fine-Tuned LLM Response Table

To highlight how useful the system is in real life, Table II shows several prompts and bilingual (Bangla + English) responses that the fine-tuned LLM made to show how useful the system is in actual life.

## IX. Discussion

Putting together vision and language portions fills a huge gap in the current ways of discovering plant diseases. The explainability module helps farmers in Bangladesh and other places like it feel more confident, and the bilingual advising system makes it easier for them to get help. LoRA doesn't need as much computer power, hence the system works well even in places with few resources.

Table II
Example prompts and fine-tuned LLM advisory responses for rice disease management.

| Prompt (Predicted Disease & Context) | Fine-Tuned LLM Response (English) | Bangla-based LLM Response (Bangla) |
|---|---|---|
| Bacterial Blight<br>Location: Mymensingh<br>Plant age: 45 days<br>Severity: Moderate<br>Farmer question: the edges of leaves are becoming white and drying in | It says that the symptoms are signs of Bacterial Blight produced by the *Xanthomonas* bacteria. Advises limiting irrigation, not touching sick plants unless absolutely necessary, cutting back on nitrogen fertilizer, and following the instructions of agricultural authorities when applying copper-based bactericides. | পাতার কিনারা থেকে সাদা বা হলদে হয়ে শুকানো ব্যাকটেরিয়াল ব্লাইটের লক্ষণ বলে ব্যাখ্যা করা হয়েছে। সেচ নিয়ন্ত্রণ, আক্রান্ত গাছে অযথা হাত না দেওয়া, নাইট্রোজেন সার কমানো এবং তামাযুক্ত ব্যাকটেরিনাশক ব্যবহারের পরামর্শ দেওয়া হয়েছে। |
| Brown Spot<br>Location: Rajshahi<br>Plant age: 40 days<br>Severity: Moderate<br>Farmer question: Small brown spots with yellow rings | Recognizes Brown Spot as a fungal illness. If the illness becomes worse, it means you should stop using too much nitrogen, improve the drainage in the field, and use fungicide. | এটি ছত্রাকজনিত ব্রাউন স্পট রোগ বলে উল্লেখ করা হয়েছে। অতিরিক্ত ইউরিয়া বন্ধ করা, ভালো নিষ্কাশন ব্যবস্থা নিশ্চিত করা এবং প্রয়োজনে ছত্রাকনাশক ব্যবহারের পরামর্শ দেওয়া হয়েছে। |
| Blast Disease<br>Location: Dinajpur<br>Plant age: 35 days<br>Severity: Moderate<br>Farmer question: Diamond-shaped gray lesions on leaves | It says that gray lesions shaped like diamonds are a sign of Blast illness. It proposes using fungicides that work on blasts, using less nitrogen fertilizer, and talking to professionals in farming. | পাতায় ডায়মন্ড আকৃতির ধূসর দাগ ব্লাস্ট রোগের লক্ষণ বলে ব্যাখ্যা করা হয়েছে। নাইট্রোজেন সার কমানো, ব্লাস্ট-নাশক ছত্রাকনাশক ব্যবহার এবং কৃষি কর্মকর্তার পরামর্শ নেওয়ার কথা বলা হয়েছে। |
| False Smut<br>Location: Gopalganj<br>Plant age: 70 days<br>Severity: Moderate<br>Farmer question: Green-yellow ball-like structures on panicles | It talks about False Smut, a fungal disease that affects rice panicles. It says to be careful with infected panicles, use less nitrogen fertilizer, and use fungicides that stop the illness from spreading before the flowers bloom. | শীষে সবুজ-হলুদ বলের মতো গুটি ফলস স্মাট রোগের লক্ষণ বলে ব্যাখ্যা করা হয়েছে। নাইট্রোজেন কমানো, আক্রান্ত শীষে সাবধানতা অবলম্বন এবং ফুল আসার আগে প্রতিরোধমূলক ছত্রাকনাশক ব্যবহারের পরামর্শ দেওয়া হয়েছে। |

## X. Conclusion

This study introduces an interpretable vision-language framework for identifying rice leaf illnesses and generating suggestions. The recommended solution is very accurate, easy to grasp, and practical in real life since it uses CNN-based classification, Grad-CAM explainability, and LLM-based bilingual coaching. Future endeavors will investigate mobile implementation and real-time field evaluation.

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