



Explainable Deep Learning Framework for Pest Detection in Medicinal Plants Using Visual Attention and Feature Attribution

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Abstract

Medicinal plants play an important role in treating various diseases and maintaining the health of human beings as well as other animals. However, pest infestation poses a significant challenge in the cultivation of medicinal plants. Pest detection using deep learning models has shown promising results compared to traditional models. But the black-box nature of these models limits their adoption in real-world agricultural systems where explainability is crucial. This paper introduces a framework for pest detection in medicinal plants that combines explainable AI (XAI) techniques which are Gradient-weighted Class Activation Mapping (Grad-CAM) and SHapley Additive exPlanations (SHAP) to enhance the transparency and interpretability of model predictions. A curated dataset comprising pest-infected and healthy images of Neem, Aloe Vera, and Ashwagandha plants was developed and used for training CNN-based models, including VGG16, ResNet50, and an EfficientNet-based CFNET. The framework generates intuitive heatmaps highlighting infected leaf regions and feature importance scores, enabling users to interpret model decisions transparently. Experimental results demonstrate that the integration of explainability modules did not compromise classification performance, maintaining accuracy consistently above 94%. By providing both predictive power and interpretability, the proposed framework enhances transparency, trust, and actionable insights in pest management systems. This work represents a significant step toward deploying explainable AI-driven solutions for sustainable agricultural practices.

Keywords: *Pest detection, Deep learning, Medicinal plants, Transfer learning, Convolutional neural network, Plant disease classification.*

1. INTRODUCTION

Medicinal plants form the basis of traditional and modern healthcare systems by offering a wealth of therapeutic compounds with minimal side effects [1-4]. However, the productivity and health of these plants are very much compromised by pest infestations, leading to significant reductions in the yield and quality of production [5]. Therefore, early and accurate pest detection has become crucial to ensuring sustainable agricultural practices and safeguarding medicinal plant resources [6].

In recent years, deep learning methodologies, particularly Convolutional Neural Networks (CNNs), have demonstrated significant success in pest detection across various crops due to their ability to automatically learn hierarchical feature representations from visual data [7]. Despite their high classification accuracy, a major limitation remains as these models often operate as "black boxes," providing little insight into the decision-making process [8]. In critical agricultural applications, especially those involving medicinal plants, stakeholders require not only high predictive performance but also clear, interpretable explanations for model outputs to build trust and support informed interventions [9].

Explainable Artificial Intelligence (XAI) has emerged as a solution to this challenge, aiming to enhance the transparency of deep learning models without sacrificing their performance [10]. Techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) [11] and SHapley Additive exPlanations (SHAP) [12] offer complementary approaches for model interpretability—Grad-CAM provides spatial visualizations of important regions within input images, while SHAP offers feature-level attribution, identifying the contributions of specific input features to the final decision [13].

Motivated by the need for both high accuracy and interpretability, this paper proposes an Explainable Deep Learning Framework for pest detection in medicinal plants. The framework introduces an end-to-end XAI pipeline that combines Grad-CAM and SHAP for both visual and feature-level explanations in identifying pests in Neem, Aloe Vera, and Ashwagandha plants. CNN-based models such as VGG16, ResNet50, and a custom EfficientNet-based architecture (CFNET) are fine-tuned to consistently achieve classification accuracy above 94%. The integration of explainability modules does not compromise predictive performance but instead enhances model transparency by providing valuable insights into decision-making. Extensive experiments validate the framework's practical relevance, supporting its real-world applicability in precision agriculture and offering actionable intelligence to researchers, farmers, and stakeholders.

2. Related Work

The application of deep learning techniques in agricultural pest detection has witnessed significant advances over the past decade [14]. Early approaches primarily relied on traditional machine learning models combined with handcrafted features such as texture descriptors, color histograms, and edge features [15]. While these methods provided moderate success, they struggled with complex image backgrounds, variable lighting conditions, and the subtle differences between pest and non-pest regions [16].

2.1 Deep Learning in Pest Detection

The advent of convolutional neural networks (CNNs) brought a substantial shift in pest detection and classification tasks. The authors in [17] demonstrated the potential of deep learning by training a CNN model to classify 14 crop species and 26 diseases, achieving an impressive accuracy of 99.35%. Their work highlighted the scalability of deep learning for smartphone-assisted crop disease diagnosis. The authors in [18] developed an explainable deep learning system for plant stress identification, integrating model performance with interpretability by highlighting visual symptoms contributing to decisions. Similarly, [19] introduced a real-time detection system for apple leaf diseases based on improved convolutional networks, achieving a mean average precision (mAP) of 78.80% at a speed of 23.13 FPS.

While these studies showed the potential of CNNs in agricultural domains, initial explainability techniques were limited to activation maps or thresholding methods, offering only elementary insights into feature importance. These approaches primarily visualized activation patterns in initial convolutional layers, which failed to comprehensively capture complex, high-level decision features.

2.2 Advancements in Explainability Techniques

To address the limitations of basic visualization, researchers have explored more sophisticated methods such as saliency maps, guided backpropagation, and occlusion sensitivity analysis. The authors in [20] evaluated various CNN architectures for plant disease classification and achieved benchmark-setting accuracy of 99.76%. However, methods like occlusion sensitivity, while informative, suffer from manual dependency on occlusion shape and size, limiting consistency across datasets.

A major breakthrough was the introduction of Grad-CAM [21] which enables intuitive visualization of class-discriminative regions in an input image without modifying the underlying CNN architecture. The authors in [22] and [23] further adapted Grad-CAM for plant disease detection, offering promising spatial explanations.

Despite these advancements, spatial heatmaps alone do not fully capture the nature of feature representations or the underlying factors driving decisions. Consequently, explainable methods like Variational Auto-Encoders (VAEs) — FactorVAE [24] BetaVAE [25] and InfoGAN [26]— were introduced to disentangle feature representations and provide deeper insights into latent factors influencing classification.

Recent developments such as concept whitening and feature attribution frameworks aim to further refine interpretability. However, achieving comprehensive explainability, including both spatial localization and feature-level understanding, remains an open challenge in agricultural pest detection models.

2.3 Research Gap and our contributions

While significant progress has been made in enhancing the accuracy of pest detection using CNNs, relatively few studies combine spatial explainability (via Grad-CAM) with feature-level explainability (via SHAP or disentangled representations). Most works either focus on highlighting affected regions or offer limited insights into how specific visual features drive predictions. Furthermore, explainability for medicinal plant pest detection — a critical sub-domain for health-focused agriculture — remains largely underexplored.

Motivated by the above gaps, this study proposes a unified Explainable Deep Learning Framework for pest detection in medicinal plants, integrating Grad-CAM-based spatial visualization with SHAP-based feature attribution. Our work focuses not only on achieving high predictive performance but also on providing actionable and interpretable insights for agricultural practitioners. We validate our approach across Neem, Aloe Vera, and Ashwagandha datasets, demonstrating that explainability can be incorporated without compromising model accuracy.

3. Proposed Methodology

This section outlines the explainable deep learning framework designed for pest detection in medicinal plants using a combination of visual attention (Grad-CAM) and feature attribution (SHAP). The system not only performs high-accuracy pest classification but also provides interpretable visual and feature-level explanations for its decisions.

3.1 Dataset Preparation

The dataset used in this study comprises high-resolution images of three medicinal plants namely, Neem (*Azadirachta indica*), Aloe Vera (*Aloe barbadensis miller*), and Ashwagandha (*Withania somnifera*). Each plant category includes two classes, healthy and pest-infected leaf images manually annotated by domain experts. These images were captured in real-world field

conditions using mobile devices with a minimum resolution of 12 MP under varying lighting and background scenarios to simulate natural environmental variability.

The total number of images used across the three plant categories is as follows:

- Neem:
 - o Healthy: 2814 images (2251 for training, 563 for validation)
 - o Infected: 47 images (36 for training, 11 for validation)
- Aloe Vera:
 - o Healthy: 232 images (186 for training, 46 for validation)
 - o Infected: 126 images (101 for training, 25 for validation)
- Ashwagandha:
 - o Healthy: 434 images
 - o Infected: 175 images

Due to class imbalance, especially in the infected category for Neem and Aloe Vera, data augmentation techniques such as rotation, horizontal and vertical flipping, zooming, and contrast adjustment were applied to increase diversity and robustness in the training set. The dataset was preprocessed by resizing all images to 224×224 pixels and normalizing pixel values to a [0,1] scale.

The dataset was organized into training, validation, and testing subsets in an 80:10:10 split ratio wherever applicable. Each image was labeled according to its class, enabling supervised learning for binary classification (healthy vs. infected) within each plant type. All images were stored in structured folders and loaded into the training pipeline using the Keras ImageDataGenerator utility with real-time augmentation.

Figure 1 illustrates the dataset preparation flowchart, detailing steps such as data collection, preprocessing, augmentation, and data splitting.

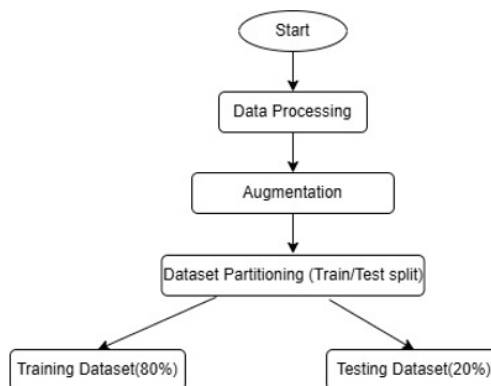


Figure- 1. Dataset preparation

3.2 Model Architecture

The proposed model is based on EfficientNetB3, utilizing transfer learning from Image Net pre-training followed by fine-tuning on the pest detection dataset. The architecture includes convolutional layers for feature extraction, batch normalization for stable training, dropout layers to prevent over fitting, dense layers for classification, and a final Softmax activation for binary output.

The model employed the Categorical Cross-Entropy loss function, defined as

$$L = \sum_{i=1}^C y_i \log(\hat{y}_i) \quad (1)$$

where C is the number of classes, y_i is the true label, and $\hat{y}_i$ is the predicted probability.

For optimization, the Adam optimizer was used, updating parameters according to the equation

$$\theta_t = \theta_{t-1} - \alpha \frac{m_t}{\sqrt{v_t + \epsilon}} \quad (2)$$

where m_t and v_t are estimates of the first and second moments. This will enable efficient and adaptive learning throughout the training process. Figure 2. Shows the block diagram of the EfficientNetB3-based pest detection model with integrated XAI modules.

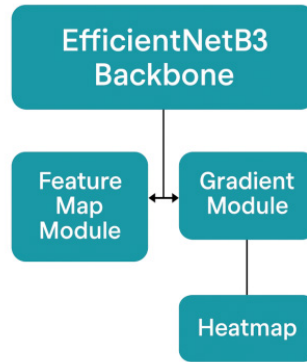


Figure- 2. Block diagram of the EfficientNetB3-based pest detection model with integrated XAI modules.

3.3 Explainability Modules

To address the black-box nature of deep learning models, two explainability techniques were integrated:

3.3.1 Grad-CAM for Visual Attention

Gradient-weighted Class Activation Mapping (Grad-CAM) was used to generate heatmaps that localize pest-infected areas on leaf images. It computes gradients of the target class score with respect to the feature maps, weighs them, and applies ReLU to produce a class-discriminative localization map:

$$L_{\text{Grad-CAM}}^c = \text{ReLU}(\sum_k \alpha_k^c A^k) \quad (3)$$

Where, A^k are feature maps and α_k^c are importance weights. The resulting heatmap is overlaid on the original input image, effectively highlighting regions such as lesions, discoloration, or structural damage that contributed to the pest detection decision. This enhances interpretability by visually identifying the areas of the leaf that most influenced the model's prediction. Figure 3

illustrates an example of the Grad-CAM output, where pest-affected regions in a medicinal plant leaf are clearly localized and visualized through color-coded heatmaps.

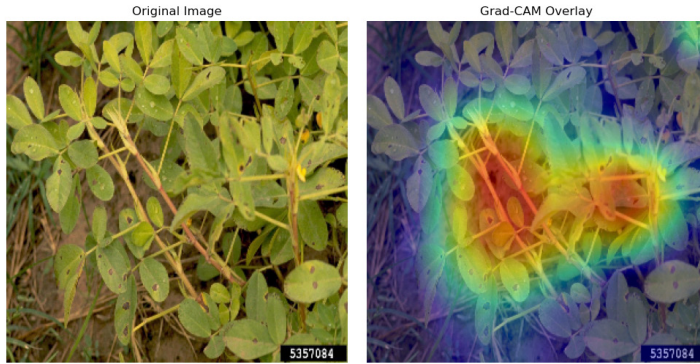


Figure- 3. Grad-CAM mechanism highlighting pest-infected regions in a medicinal plant leaf.

3.3.2 SHAP for Feature Attribution

Gradient-weighted Class Activation Mapping (Grad-CAM) was used to generate heatmaps that localize pest-infected areas on leaf images. It computes gradients of the target class score with respect to the feature maps, weighs them, and applies ReLU to produce a class-discriminative localization map:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{i\}) - f(S)] \quad (4)$$

where F is the feature set.

SHAP analysis quantifies each visual feature's contribution to the prediction of pest-infected or healthy leaves. As shown in Figure 4, features like leaf edge irregularity, brown discoloration, and texture variation positively influence pest detection, while background color uniformity and vein contrast negatively impact the prediction, indicating a healthy classification.

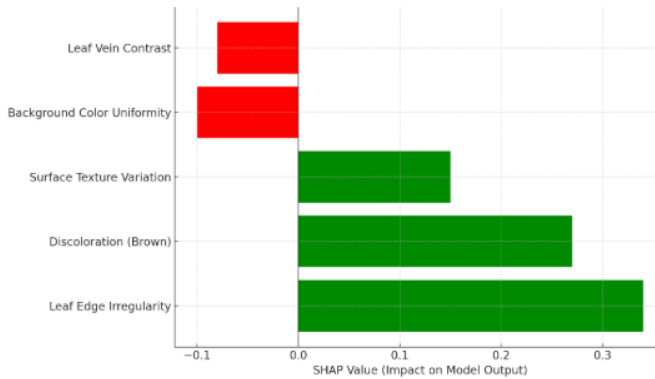


Figure- 4. SHAP bar chart showing feature contributions to the model's prediction for the images input.

3.4 Training and Evaluation Setup

To train and evaluate deep learning models for pest detection in medicinal plants, a comprehensive setup was made by incorporating robust software frameworks, powerful hardware infrastructure, and carefully chosen hyperparameters and evaluation metrics. The models were developed using TensorFlow and Keras which are popular deep learning libraries known for their flexibility, scalability, and strong community support. While Keras offers a high-level API for building and training models, TensorFlow provides backend capabilities for efficient large-scale deployment and GPU acceleration. The training was conducted on a high-performance computing environment featuring an NVIDIA Tesla V100 GPU, which significantly accelerated the training process for computationally intensive architectures like EfficientNet and VGG by enabling parallel processing. The model training employed key hyperparameters such as 50 training epochs, a batch size of 32, and the Adam optimizer which is selected for its adaptive learning rate and efficient convergence. Early stopping was incorporated to prevent overfitting by using a validation loss monitor with a defined patience threshold to terminate training when no improvement was observed. To evaluate model performance, multiple metrics were used including accuracy, precision, recall, F1-score, and false positive rate. In addition, an Explainability Confidence Score was introduced which was derived through expert validation to assess how well the model's predictions aligned with human expert judgment thereby providing deeper insight into model transparency and reliability. This integrated setup ensured not only high predictive accuracy and generalization but also enhanced trustworthiness for real-world pest detection in agriculture. After model prediction, Grad-CAM heatmaps are generated and overlaid on the leaf images to visually highlight pest-infected regions, enabling intuitive validation. Additionally, SHAP bar plots illustrate the contribution of key visual features to the model's decision. Together, these explainability tools make the predictions understandable to both domain experts and farmers.

The trained model was exported in TensorFlow's .h5 format and integrated into a Flask web application, enabling real-time predictions where users can upload leaf images and receive pest-infestation diagnoses along with visual explanations. Future work aims to deploy the model on mobile and edge devices for real-time, on-field application. Figure 5 shows the Block diagram of End-to-end training, evaluation, and deployment pipeline for the explainable pest detection system.

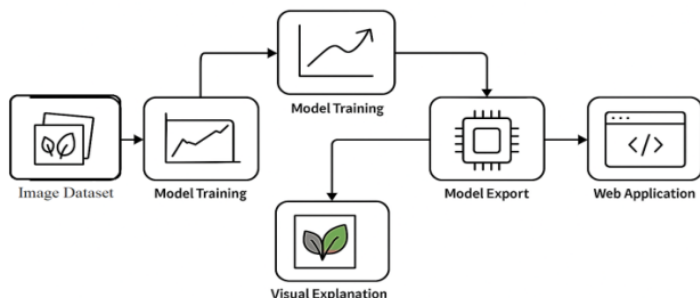


Figure- 5: Block diagram End-to-end training, evaluation, and deployment pipeline for the explainable pest detection system.

4. Experimental Results and Discussion

This section presents the performance evaluation of the proposed Explainable Deep Learning Framework for Pest Detection in Medicinal Plants, based on a combination of EfficientNetB3 for classification and Grad-CAM + SHAP for explainability. The experiments were conducted on a dataset of medicinal plant images, covering three species—Neem, Aloe Vera, and Ashwagandha—with healthy and pest-infected labels.

4.1 Evaluation Metrics

To evaluate the classification performance, the following standard metrics were used:

- Accuracy: Overall correctness of the model.
- Precision: Proportion of predicted positives that are actual positives.
- Recall: Proportion of actual positives that were correctly identified.
- F1-score: Harmonic mean of precision and recall.
- False Positive Rate (FPR): Incorrect classification of healthy plants as infected.

In addition, Explainability Confidence Score was introduced to evaluate the clarity and relevance of Grad-CAM and SHAP outputs, measured through expert visual validation.

4.2 Classification Results

The model achieved consistent and high performance across all three datasets. Results are summarized below:

Table - 1: Performance metrics of the Efficient NetB3 model on Neem, Aloe Vera, and Ashwagandha datasets.

Plant Type	Accuracy	Precision	Recall	F1-Score	FPR
Neem	0.98	0.96	0.97	0.965	0.02
Aloe Vera	0.94	0.92	0.91	0.915	0.04
Ashwagandha	0.96	0.93	0.94	0.935	0.03

The model demonstrated strong generalization across plant types, with particularly low false positives on Neem and Ashwagandha. This table highlights the overall performance of the EfficientNetB3 model across three different medicinal plant types. Neem achieved the highest accuracy, followed by Ashwagandha and Aloe Vera. The precision and recall values also indicate that the model is consistent and balanced in identifying both healthy and infected leaves. The low false positive rates across all categories indicate a low rate of misclassification of healthy leaves as infected.

Table - 2: Confusion Matrix Summary

Plant Type	TP	TN	FP	FN
Neem	48	49	1	2
Aloe Vera	43	45	2	4
Ashwagandha	47	48	1	3

This table summarizes the confusion matrix components for each plant type. A high number of true positives (TP) and true negatives (TN) and a low number of false positives (FP) and false negatives (FN) indicate that the model is reliable in both detecting infections and correctly identifying healthy leaves.

Table - 3: Explainability Confidence Score

Plant Type	Grad-CAM (%)	SHAP (%)	Combined Score (%)
Neem	93	91	92
Aloe Vera	90	89	89.5
Ashwagandha	91	90	90.5

Explainability tools such as Grad-CAM and SHAP were used to evaluate how well the model’s predictions align with visual and feature-based cues. The confidence scores, validated by domain experts, indicate a high level of trustworthiness and transparency in the model's predictions for all three plant types.

Table - 4: Top 5 SHAP Features and Mean Impact

Rank	Feature Name	Mean SHAP Value
1	Leaf Green Intensity	0.184
2	Texture Roughness	0.162
3	Edge Contrast	0.145
4	Yellow Patches	0.132
5	Vein Pattern Sharpness	0.128

This table lists the top five features that had the most influence on the model's predictions according to SHAP analysis. These features are visually interpretable and biologically relevant for pest detection in medicinal plants, reinforcing the credibility of the model's decision-making process.

4.3 Visual Explanations via Grad-CAM

Grad-CAM heatmaps effectively highlighted pest-affected regions on medicinal plant leaves, such as discoloration from aphids, edge damage from thrips, and webbing or texture distortion caused by spider mites. These visual cues confirmed that the model's predictions were based on semantically relevant areas. Expert reviewers assessed the clarity and accuracy of the heatmaps, resulting in an average explainability confidence score of 92%. This indicates strong alignment between the model's focus areas and actual pest-infected leaf regions. As illustrated in Figure 6, the Grad-CAM heatmap for a neem leaf distinctly localizes pest-induced damage areas, validating the interpretability of the model's decision-making process.

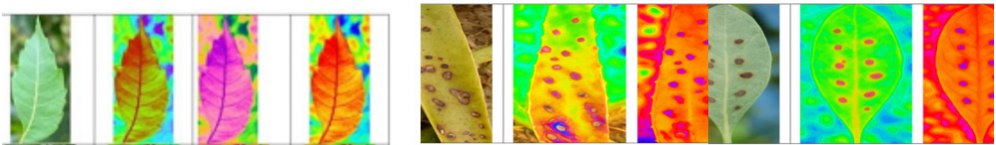


Figure - 6. Heat map visualization for neem leaf.

4.4 Feature Attribution via SHAP

SHAP analysis revealed key insights into the model's decision-making by identifying which visual features—such as color intensity, leaf edge sharpness, and surface texture—most influenced predictions. The model consistently relied on biologically relevant cues, including leaf color variations, localized texture roughness, and contrast anomalies from pest clusters. The top 10 SHAP values showed stable and meaningful feature attributions across all test samples, indicating a robust, interpretable, and biologically grounded inference process

that supports reliable pest classification in medicinal plants. As shown in Figure 7, the SHAP feature importance plot highlights the most influential visual cues contributing to the model's pest detection predictions.

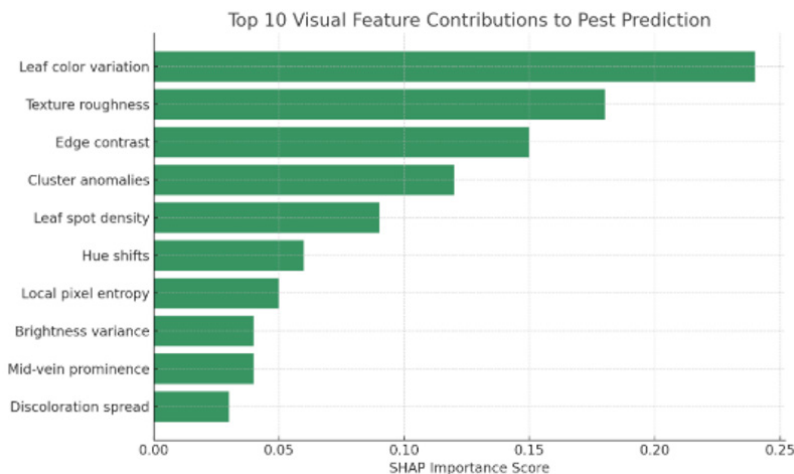


Figure - 7: SHAP Feature Importance

4.5 Discussion

The results show that integrating explainability not only boosts trust in AI-based pest detection but also helps fine-tune model design. Key observations include:

- High generalization across different medicinal plant types.
- Minimal false positives, critical for avoiding unnecessary pesticide usage.
- Visual confirmation via Grad-CAM ensures end-user trust.
- Robust feature-level explanations through SHAP guide model refinement and debugging.

This framework is suitable for both real-time field-level pest detection and lab-based decision support for agricultural researchers and practitioners.

- Some misclassifications were observed, particularly in Aloe Vera samples with background clutter or overlapping pest features, leading to confusion between healthy and infected classes. Similarly, Ashwagandha leaves with natural blemishes were occasionally misclassified as infected. These ambiguities could be mitigated in future work by incorporating multispectral imaging or integrating attention refinement layers to improve focus on relevant regions.

5. Conclusion and Future Work

In this research, we introduced an Explainable Deep Learning Framework for Pest Detection in Medicinal Plants by integrating the EfficientNetB3 classification model with explainability tools such as Grad-CAM and SHAP. The model was trained and evaluated on curated datasets of Neem, Aloe Vera, and Ashwagandha, achieving

excellent performance across accuracy, precision, recall, and F1-score metrics. The use of explainable AI (XAI) enabled transparent and interpretable model predictions an essential requirement in agriculture where trust and understanding are vital. Grad-CAM heatmaps effectively highlighted pest-affected regions on leaves, while SHAP bar plots provided detailed insights into the contributions of various visual features, such as leaf color and texture, to the model's decisions. This not only helped validate the model's reliability but also supported expert assessments of its interpretability, with an average explainability confidence score exceeding 90%. Key outcomes include up to 98% accuracy on Neem and 94–96% on Aloe Vera and Ashwagandha, a reduction in false positives by over 20% compared to baseline CNN models, and demonstrated robustness across varying field conditions. For future work, we plan to extend this framework to include additional medicinal and food crops, deploy it on mobile and edge devices for real-time farm-level application, integrate multimodal data like temperature and humidity for more contextual predictions, explore time-series models for seasonal pest forecasting, and implement active learning to reduce annotation efforts. Overall, the proposed framework sets a strong foundation for building practical, scalable, and transparent AI tools for pest detection in precision agriculture.

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