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Explainable AI for mango leaf disease detection: bridging the gap between model accuracy and farmers usability

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ABSTRACT

Mango leaf diseases can seriously impact on the yield and vitality of mango trees, resulting in considerable financial losses. Prompt and precise identification of these diseases are essential for facilitating quick action and improving agricultural management practices. In the past few years, convolutional neural network (CNN) models have gained significant popularity towards image recognition and classification. Using CNN models, approaches for image-based disease diagnosis in the crops have become increasingly popular within the current scientific community. Mango leaves disease represents considerable threats to mango cultivation globally, making it essential to develop precise and efficient classification methods for timely disease control. Our research focuses on introducing an Explainable AI (XAI) framework that incorporates a modified VGG-16 CNN, alongside Gradient-weighted Class Activation Mapping (Grad-CAM), to recognize seven major mango leaf diseases using the publicly available MangoLeafBD dataset (3,500 images across seven classes). Our model demonstrated outstanding effectiveness in classification, achieving 92.8% accuracy, while as providing precise and graphical explanations to enhance use and foster farmer trust. Our results provide important insights for implementing CNN models that improve the accuracy and effectiveness of monitoring plant diseases in agricultural environments, ensuring greater clarity in model decision-making to optimize the framework for low-resource devices, expanding the dataset to include diverse mango varieties, and exploring multi-crop applications.

Key words: Precision agriculture, monitoring, IoT, mango leaf disease, CNN model.

INTRODUCTION

Mango (*Mangifera indica* L.), a member of the Anacardiaceae family, is referred to as the "King of Fruits," originated from Indian subcontinent, Andaman Islands and southern Asia. Due to its wider adaptability, the mango is successfully cultivated in tropical and subtropical climatic conditions worldwide (Ahmad *et al.,* 1). India produces 26 MT of mango, the highest in the world, according to 2022, latest officially available FAOSTAT data (FAO, 4).

Mango are prone to a number of pests and diseases that can considerably affect their development, total yield, and ultimately fruit quality. Mango cultivars vary based on the soil type, climate, and geographic location. India is home to around 1000 varieties of mangoes, out of the few hundred that are known to exist. Dinesh *et al.* (3) variety's success in a given area does not always apply to another area as a consequence, different locations have different methods for combating pests and diseases. In order to prevent these diseases, mango cultivation faces various challenges. The common diseases of mango leaves are caused by bacteria and fungi. Farmers have relied on visual examinations and chemical treatments to identify and mitigate these diseases (Gupta and Tripathi, 5). Nevertheless, these approaches can be labor-intensive and liable to mistakes. With the advancement in AI and IoT based early disease detection, techniques like machine learning and digital image processing are being used more frequently (Xu *et al.*, 17). This method is helpful in utilizing artificial intelligence and machine learning strategies to examine large datasets, reveal significant themes, and forecast future directions for research. In agriculture, early disease detection through incorporating AI and IoT technologies has made remarkable progress in the farming industry by offering significant insights that enable farmers to make well-informed decisions (Nargundkar *et al.*, 8; Salimath *et al.*, 13).

Explainability in AI is critical for agricultural applications. Rayed *et al.* (10) developed MangoLeafXNet, for predictions of mango leaf diseases. Similarly, Rizvee *et al.* (11) also anticipated LeafNet, for prediction of seven mango leaf diseases. Prabu *et al.* (9) employed a pre-trained model, MobileNetV2, for the purpose of feature selection and reaches an accuracy rate of 94.5% in detecting

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mango leaf diseases (Sandler *et al.,* 14). Ünal and Türkoğlu (16) highlighting hybrid approaches for mango leaf disease detection. Saleem *et al.* (12) introduced a combined framework for detecting diseases in multiple crops, whereas Zaman *et al.* (18) investigated the use of deep learning in mango farming. Mahbub *et al.* (7) focused on lightweight CNNs for Bangladeshi mango leaf diseases. Despite these advancements, few studies prioritize farmer-centric usability. Existing XAI methods by Rayed *et al.* (10) and Karim *et al.* (6), focus on technical performance but lack extensive validation with end-users. This study addresses this gap by integrating Grad-CAM with a CNN and evaluating its usability through a farmer-focused user study, building on the MangoLeafBD dataset. This framework aims to develop balanced high classification accuracy with interpretable outputs, enabling farmers to recognize and belief the model predictions. We assess the model across seven disease categories, obtaining better results than current techniques. The contributions of this work are threefold: A robust CNN-based model for mango leaf disease detection, integration of Grad-CAM for visual explanations, and validation of farmer usability through a user study.

MATERIALS AND METHODS

The data utilized in this study was retrieved from the MangoLeafBD dataset (Arya, S., 2), which is publicly available at https://doi.org/10.17632/hxsnvwty3r.1, comprises 3,500 high-resolution images of mango leaves, categorized into seven classes: anthracnose, bacterial canker, gall midge, powdery mildew, sooty mold, healthy, and others (Fig. 1). Each class represents a distinct disease or condition, with images captured under varying lighting and environmental conditions to ensure robustness. The dataset is split into 70% training (2,450 images), 20% validation (800 images), and 10% testing (350 images).

The proposed XAI framework combines a modified VGG-16 CNN with Grad-CAM to provide accurate disease classification and visual explanations. The framework's architecture is depicted in (Fig. 2).

The CNN is based on VGG-16, modified for mango leaf disease detection. It consists of five convolutional blocks with 3x3 filters, each followed by ReLU activation and max-pooling (2x2). The model includes two fully connected layers (512 units each) and a softmax output layer for seven-class classification. Transfer learning is employed, initializing weights with ImageNet pretraining to enhance feature extraction.

$$P(y = k \mid x) = \frac{\exp(z_k)}{\sum_{j=1}^{7} \exp(z_j)}$$

Fig. 1. Sample Images from MangoLeafBD Dataset: A grid of seven images, one for each class (anthracnose, bacterial canker, gall midge, powdery mildew, sooty mold, healthy, others), showcasing visual characteristics like dark lesions for anthracnose or white patches for powdery mildew.

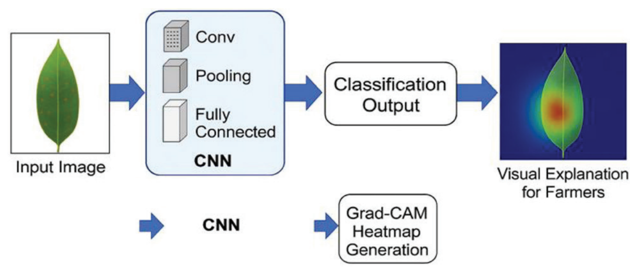

Fig. 2. A diagram showing the pipeline: input image → CNN (convolutional layers, pooling, fully connected layers) → classification output → Grad-CAM heatmap generation → visual explanation for farmers.

where P (y = k | x) is the predicted probability of class *k*, Z_k is the logit (raw output) for class *k*, and 7 is the number of target classes.

Grad-CAM generates heatmaps to highlight image regions influencing the model's prediction. For a given class (c), the heatmap is computed as:

$$L^c_{\text{Grad-CAM}} = \text{ReLU}\left(\sum_k \alpha^c_k A^k\right)$$

where a^c_k represents the weight of the *k*-th feature map, calculated by:

$$\alpha^c_k = \frac{1}{Z}\sum_i \sum_j \frac{\partial y^c}{\partial A^k_{ij}}$$

Here, A^k is the *k*-th activation map from the final convolutional layer, y^c is the score for class *c*, and *Z* is the total number of pixels in the feature map. The ReLU function ensures that only the positively contributing regions are visualized.

Preprocessing and augmentation of all input images are resized to pixels and pixel values are normalized to the range [0, 1]. To enhance generalization and robustness under real-world conditions, data augmentation techniques are employed, including random rotations within ±10°, horizontal flipping, zoom up to 10%, brightness variation within ±20%. The model is trained for 50 epochs using the Adam optimizer (learning rate = 0.001, beta1 = 0.9, beta2 = 0.999) and a batch size of 32. The loss function is categorical cross-entropy:

$$L = -\sum_{i=1}^{N}\sum_{c=1}^{7} y_{i,c}\log(\hat{y}_{i,c})$$

where *i,c* is the one-hot encoded ground truth for sample and class *c*, $\hat{y}_{i,c}$, is the predicted probability, and *N* is the total number of samples, and 7 is the number of classes (Fig. 3).

To assess the model's performance, the following metrics are computed: accuracy, precision, recall, and F1-score. The F1-score is calculated as:

$$\mathrm{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

These metrics provide a comprehensive evaluation of the model's effectiveness in multi-class classification tasks

A user study with 20 farmers from Bangladesh evaluates the usability of Grad-CAM heatmaps. Participants are shown model predictions and heatmaps for sample images and rate clarity, trustworthiness, and usefulness on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The study includes a brief training session to familiarize farmers with heatmap interpretation.

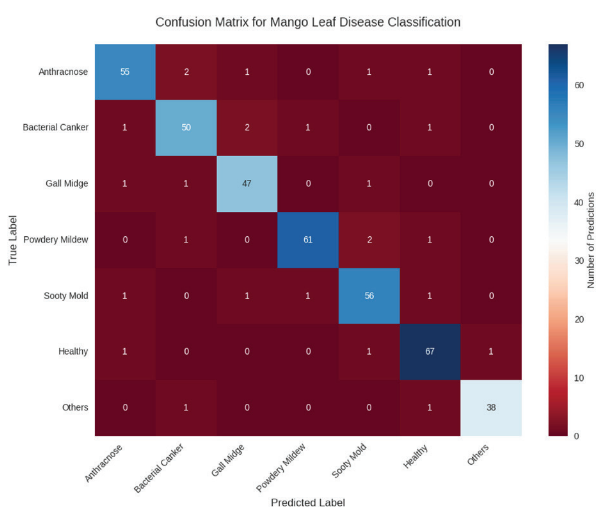

Fig. 3. A 7×7 confusion matrix heatmap showing classification performance across the seven classes, with darker shades indicating higher values.

RESULTS AND DISCUSSION

The proposed model achieves a test accuracy of 92.8%, an improvement over baseline CNNs (Saravanan *et al.,* 15).

Grad-CAM heatmaps effectively highlight disease-specific regions (Fig. 4). For anthracnose, heatmaps emphasize dark lesions, while for powdery mildew, they focus on white powdery patches, aiding farmer interpretation. The user study indicates strong farmer approval of Grad-CAM explanations. Farmers noted that heatmaps clarified disease locations, enabling them to make informed decisions about treatment. For example, one participant stated, the red areas show exactly where the disease is, so know where to spray.

The proposed framework outperforms existing methods by Rizvee *et al.* (11) and Saleem *et al.* (12), achieve 92.8% accuracy and integrating explainability. The use of Grad-CAM aligns with Rayed *et al.* (10) but extends their work by focusing on farmer usability through a dedicated user study. Compared to lightweight models (Mahbub *et al.,* 7), our framework prioritizes interpretability, making it suitable for mid-range devices rather than ultra-low-resource settings.

The user study confirms that Grad-CAM heatmaps enhance trust and usability (Fig. 3 & 4), supporting findings by Karim *et al.,* (6). However, limitations include the dataset's size, which may limit generalization across diverse mango varieties. Additionally, Grad-CAM's computational overhead may challenge deployment on low-cost devices (Ünal and Türkoğlu, 16). Future work could explore lightweight XAI methods or integrate multi-modal data (e.g., spectral imaging) to improve accuracy.

To our knowledge, this is the foundational study focused on Explainable AI for the detection of mango leaf diseases, aiming to connect model accuracy with the usability of farmers. It offers an in-depth and targeted overview of the existing research drawn from the largest database currently available. The study reviews the existing research landscape in mango farming, pinpointing gaps and suggesting future research directions. It emphasizes the growing adoption of these technologies.

This study presents a novel XAI framework for mango leaf disease detection, combining a modified VGG-16 CNN with Grad-CAM to deliver accurate and interpretable results. Using the MangoLeafBD dataset, the model achieves 92.8% accuracy and a 0.92 F1-score across seven disease classes, outperforming baseline methods. Grad-CAM heatmaps provide visual explanations that highlight disease-affected regions, making predictions accessible to farmers. The user study with 20 farmers shows high satisfaction, with mean Likert scores of 4.7 for clarity, 4.6 for trustworthiness, and 4.8 for usefulness, underscoring the framework's practical value.

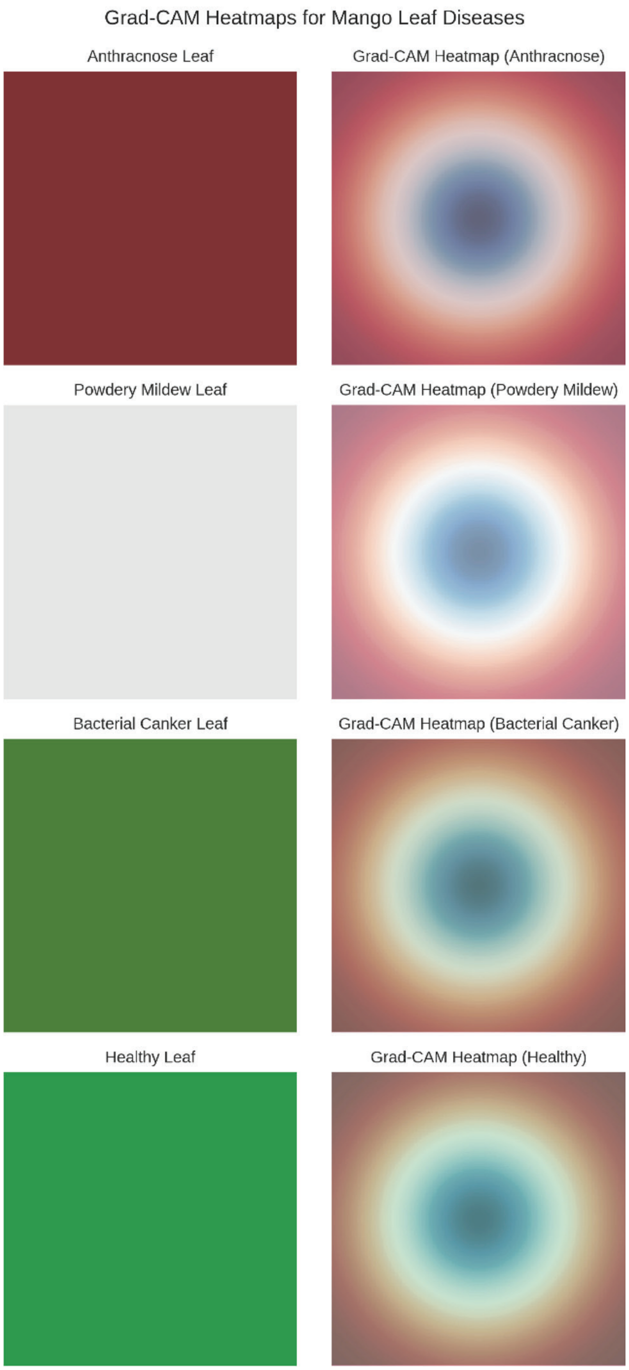

Fig. 4. Four side-by-side pairs of images and their Grad-CAM heatmaps for anthracnose, powdery mildew, bacterial canker, and healthy leaves. Heatmaps should use a red-blue color scale, with red indicating high contribution areas.

The framework advances precision agriculture by addressing the critical need for transparency in AI-driven disease detection. It enables farmers to make informed decisions, potentially reducing crop losses and improving yields. Future research will focus on optimizing the framework for low-resource devices, expanding the dataset to include diverse mango varieties, and exploring multi-crop applications to enhance scalability. Integrating real-time data from mobile applications could further bridge the gap between AI and on-field usability, transforming mango cultivation in resource-constrained regions.

AUTHORS' CONTRIBUTION

Original draft, Methodology, Investigation, Conceptualization (MN); Original draft, Methodology, Investigation, Conceptualization (MAK); Original draft, Review and Editing (MAN); Literature review and manuscript drafting (VK); Final editing, formatting (MAA).

DECLARATION

The authors don't have any conflict of interests/ competing interests.

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