Explainable Intelligent Detection of Tomato Leaf Diseases: An Explainable Deep Learning Approach

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***Abstract*—Plant diseases are one of the most significant threats to global food security, impacting food availability and safety, as well as their negative impact on agricultural productivity. Addressing this major challenge requires the development of advanced and modern disease diagnostic equipment that not only detects but also accurately identifies disease. In this paper, we propose an innovative algorithm based on transfer learning for the detection of tomato leaf diseases. Convolutional Neural Networks (CNNs) were used in conjunction with pre-trained models such as EfficientNetB3, Xception, and MobileNetV2 to accurately classify and diagnose diseases. Experimental results demonstrated high classification accuracy, reaching 0.93 for CNN, 0.94 for MobileNetV2, 0.95 for Xception, and 0.995 for EfficientNetB3. Using machine learning and image processing techniques, the system can quickly and automatically diagnose disease symptoms on plant leaves, providing farmers with up-to-date and reliable information on what to do. The research also addresses the interpretability of the model by applying Saliency Maps and Grad-CAM (Gradient-Weighted Class Activation Mapping) techniques to visually explain the model's decisions, which enhances transparency and increases user confidence in the Artificial Intelligence (AI)-based system in the agricultural field.**

***Keywords*—machine learning techniques, convolutional neural network, image diagnostic, saliency maps, Grad-CAM, explainable AI, leaf disease detection**

I. INTRODUCTION

Globally, agriculture is constantly threatened by plant diseases, which can jeopardize food security, hamper agricultural productivity, and threaten the safety of people's food supplies [1]. Innovative disease detection methods are essential to effectively address such challenges. We propose a novel approach for disease detection in tomato leaves based on deep transfer learning techniques. Our research exploits the capabilities of Convolutional Neural Network (CNN) [2], which are deep learning models widely recognized for their success in image recognition tasks. In particular, we explore the use of pre-trained models [3–5], including EfficientNetB3, Xception, and MobileNetV2 [6], to identify and classify tomato leaf diseases. Through extensive experimentation, we demonstrate the strong performance of these models: CNNs achieve an accuracy of 0.93, EfficientNetB3 reaches 0.995, MobileNetV2 scores 0.94, and Xception attains 0.95.

Our contribution goes beyond high classification accuracy. We present an integrated system that combines machine learning techniques [7–12] and advanced image processing methods [13], enabling rapid diagnosis of tomato leaf diseases at the earliest visible signs on leaves or plantsIt efficiently diagnoses ailments in crops, provides the requisite information to farmers at the right time for their actions as well as targeted treatments, thus making crop management more effective. Furthermore, this study emphasizes model interpretability using importance maps [14] and Grad-CAM (Gradient-Weighted Class Activation Mapping) [15] in the deep learning models. This will not only increase the credibility of the AI-based system, but will also enhance the confidence of end users, especially those working in the agricultural field [16]. In short, this work paves the way for explainable Artificial Intelligence (AI) in agriculture for early disease detection and supporting efforts to enhance global food security.

The following is a summary of this study's significant contributions:

- Developing a novel and unique deep learning-based technique to identify diseases in tomato leaves through pre-trained convolution neural network models; evaluating several pre-trained models and comparing the resultant efficacy of our method with the highest retrieval of EffectiveNetB3 (0.995).
- Autoedmatically identifies diseases and provides information to farmers within a very short time for targeted treatment and precise management of crop health.
- Using importance mapping and Grad-CAM, it will bring transparency and trust in AI-powered disease detection through the validation of model

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interpretability and demonstration of the decision-making process of the model.
- Thus, a transparent and credible agricultural disease detection system has been established in this study.

II. Literature Review

Recent developments indicate the application of wide varieties of deep learning approaches in tomato leaf disease detection domains. Holzinger and Too [17, 18] developed a custom Convolutional Neural Network (CNN) that registered 91.2% accuracy, outperforming pre-trained models. Transfer learning via Inception-V3 yielded phenomenal results, with training accuracy equivalently touching 99.58% and testing accuracy hitting 97.19% while detecting different tomato leaf diseases [19].

Starting in 2022, Vision Transformers (ViTs) have been introduced into agricultural tasks. Doshi, Smith, Khan and Ramesh [20–23] used a pre-trained ViT model to classify ten tomato diseases with an accuracy of 97.9%, showcasing the ability of ViTs to capture global contextual relationships within images. In parallel, Masked Autoencoders (MAE) were explored for unsupervised pre-training, reducing the need for manual annotations. Das [24] showed that a pre-trained MAE model achieved 95.4% accuracy on a noisy subset of PlantVillage, compared to 91% for a standard CNN.

Hybrid approaches combining CNN, Long Short Term Memory (LSTM) and attention mechanisms have also been explored to account for the temporal dynamics of symptom progression.

Furthermore, Generative Adversarial Networks (GANs) have been incorporated to enhance data augmentation. Simonyan [25] generated synthetic images of diseased leaves, boosting the accuracy of a CNN classifier from 94.3% to 97.2%. These methods have proven especially effective in addressing class imbalance and the scarcity of certain diseases. Das [3] ocused on enhancing accuracy and reducing computational time through feature fusion, achieving 94% accuracy with a random forest classifier. Jiang *et al.* [26] improved ResNet-50's performance by modifying activation functions, achieving 98.3% training and 98.0% testing accuracy. While classical augmentations such as rotation, flipping, and cropping already improve the generalization capability of deep learning models, their effectiveness remains limited in scenarios with severe class imbalance or small training sets. In such cases, generative approaches, particularly Generative Adversarial Networks (GANs), can provide an additional benefit by synthesizing realistic images that increase intra-class diversity. Recent studies have shown that incorporating GAN-generated samples can enhance recall for minority classes and improve robustness under real-field conditions (e.g., variations in lighting, background, or image quality) [27–29]. Reported gains typically range from +1 % to +4 % in macro-F1 or minority class recall, and up to +5 % on out-of-distribution test sets [29]. However, GAN-based augmentation also carries risks, such as producing artifacts that may lead to overfitting or shortcut learning. Therefore, synthetic images should be used only as a complement (around 20–30 % of the training set) and never in validation or test sets. Moreover, recent literature suggests benchmarking generative augmentation against strong non-generative methods such as RandAugment, MixUp, or CutMix, which can often provide comparable improvements without introducing synthetic artifacts.

TM *et al.* [30] proposed a modified LeNet model with 94–95% accuracy, emphasizing computational efficiency. Ashok *et al.* [31] achieved a 98% accuracy rate with a CNN algorithm, optimizing leaf portion parameters during training. Bhujel *et al.* [5] integrated attention modules, with the Convolutional Block Attention Module (CBAM) leading with 99.69% average accuracy. Bhandari *et al.* [4] utilized EfficientNetB5, attaining high accuracy and employing gradient- weighted class activation mapping for model interpretability. These studies collectively contribute to advancing fast and accurate tomato leaf disease diagnosis with Deep Learning (DL) techniques.

III. Proposed Methodology

In this section, we present a deep learning model developed to identify diseases in tomato leaves. The architecture is based on Convolutional Neural Networks (CNN), incorporating three convolutional layers followed by maximum pooling layers, with each layer using a different number of filters.

For this experiment, we utilized the Plant Village dataset, which includes nine disease categories and one category containing only healthy tomato leaf images. The workflow of the proposed method is illustrated in Fig. 1.

A. Dataset Collection

This study analyzed ten different tomato diseases, nine of which affect tomato leaves, and one class representing disease-resistant tomatoes. The dataset, sourced from PlantVillage, included 50,000 images of 14 crop types, with a focus on tomatoes. Several images from various tomato classes were used. The nine major tomato diseases studied were Target Spot, Mosaic Virus, Bacterial Spot, Late Blight, Leaf Mold, Two-Spotted Spider Mite, Yellow Leaf Curl Virus, Early Blight, and Septoria Leaf Spot.

The dataset comprised 12,250 training images, 2625 validation images, and 2625 test images, with an even distribution of images across disease classes. Fig. 2 shows the dataset utilized by our proposed model.

B. Data Preprocessing

To prepare our dataset for training the CNN classifier, we performed essential preprocessing steps. Initially, we resized all images to a uniform 256×256 pixel size. Subsequently, we converted the images to grayscale. This preprocessing aimed to standardize the image format and facilitate feature extraction by the model. Next, we classified the tomato leaf images into ten distinct classes, each representing a different disease. To process the images, we used the cv2.imread() function to read them in and the cv2.resize() function to resize them to a suitable size of 150×150 pixels due to memory limitations. After loading and preprocessing the images, we split the dataset into a training set, a validation set and test set, maintaining an 70:15:15 ratio and resizing. We then converted the images to array format using the np.array() function. Additionally, we assigned unique labels to each plant image using the LabelBinarizer() function. Finally, we split the Plant Village tomato leaf dataset into two sets: a training set and a validation set. Finally, tomato leaf images from the entire PlantVillage dataset were prepared and segmented for training and validation purposes.

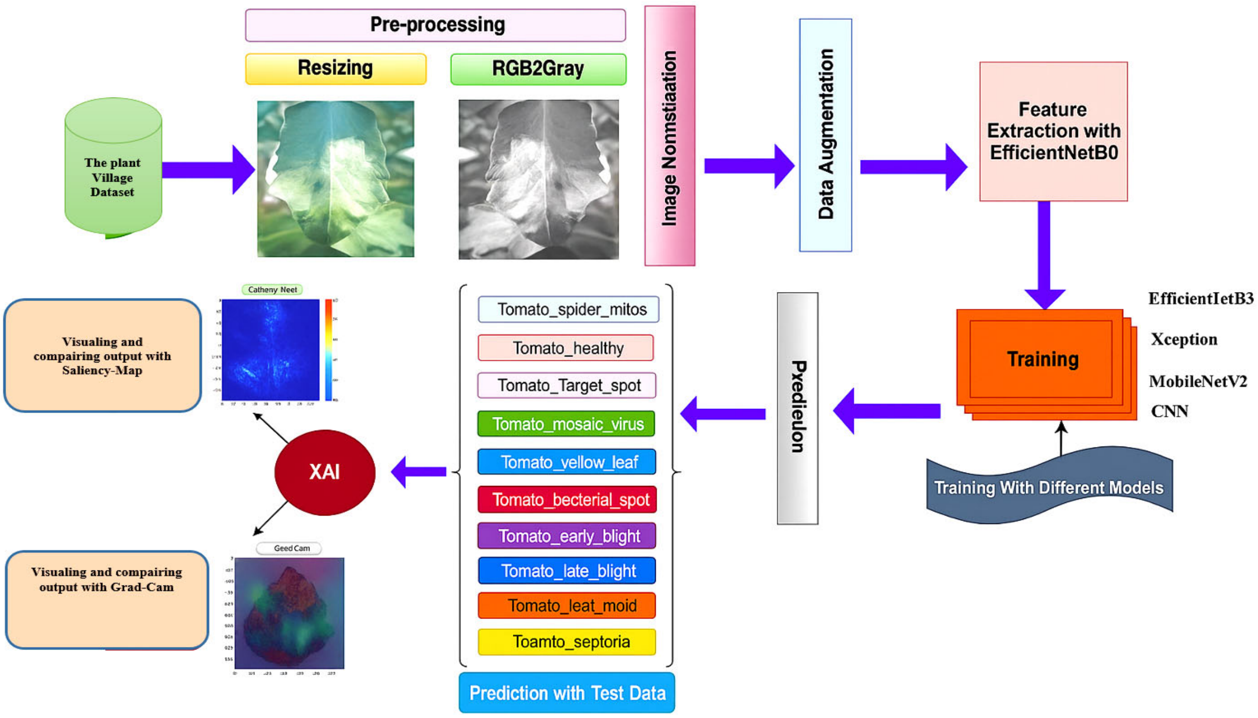

Fig. 1. Flowchart of the proposed experiment methodology.

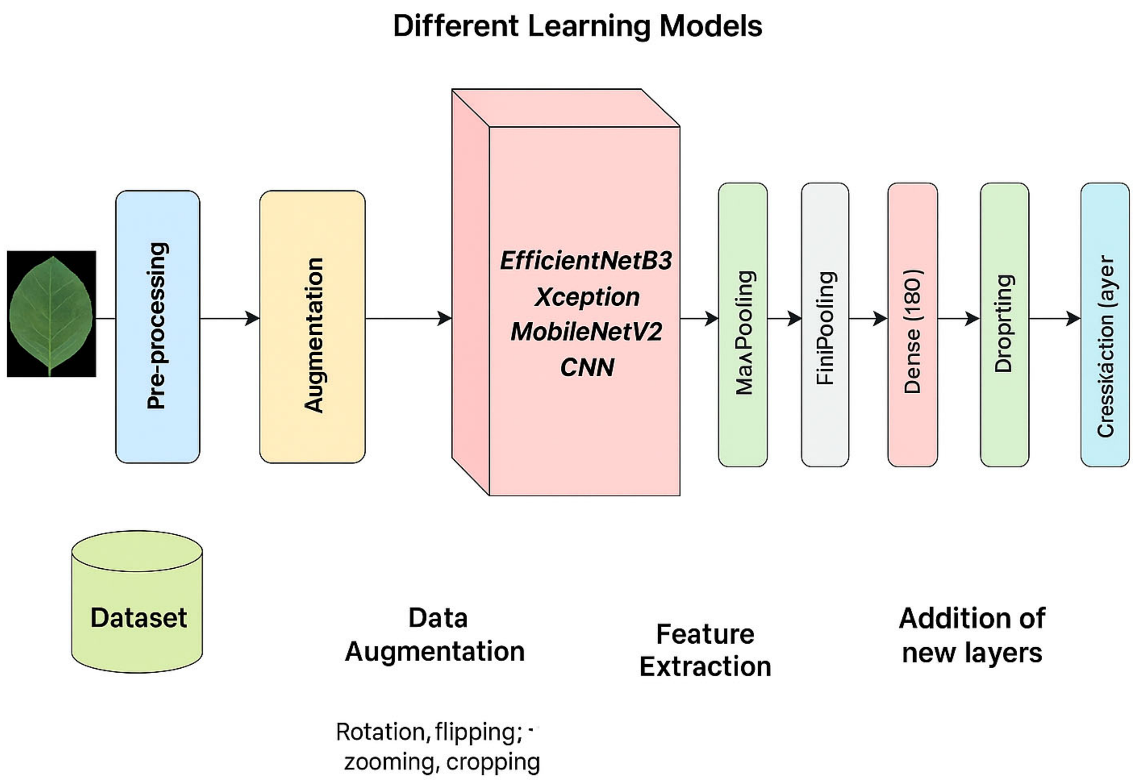

Fig. 2. Transfer learning operation.

C. Data Augmentation

Data augmentation enhances model robustness by artificially expanding the training dataset using transformations such as rotations, flips, and noise addition. More advanced approaches include the use of GANs or autoencoders to create synthetic samples. These techniques are particularly effective in scenarios with scarce labeled data, as they help reduce overfitting and improve generalization performance to address class imbalance, we applied data augmentation techniques using Python's Augment or package [32]. When a class had fewer than 1000 images, we generated new images by rotating, flipping, cropping, and resizing the existing ones.

This method was implemented on both the training and validation datasets, maintaining a uniform distribution of 1225 images per class for training and 263 for validation. All images were resized to 150×150 pixels and stored in JPEG format.

D. Features Extraction

We utilized pre-trained EfficientNet models [33] for feature extraction, capitalizing on their expertise in image recognition tasks. By employing EfficientNetB0, we processed the tomato leaf images to extract features across several hierarchical levels, capturing fine details and disease-specific patterns. The discriminative features extracted are essential to the effectiveness of our tomato leaf disease detection system, serving as the foundation for precise disease classification and categorization in the following stages of the model.

E. Convolution Neural Network

TABLE I. BASIC CNN MODEL DESCRIPTION

Component	Technical Details
Model Type	Sequential
Input Size	256×256×3
Transfer Learning	Yes—pre-trained model used as base
1st Convolution	256×256; kernel (3×3); ReLU; padding = 'same'
1st MaxPooling	127×127; pooling size: (2×2)
2nd Convolution	125×125; kernel (3×3); ReLU; padding = 'same'
2nd MaxPooling	62×62; pooling size: (2×2)
3rd Convolution	60×60; kernel (3×3); ReLU; padding = 'same'
3rd MaxPooling	30×30; pooling size: 2×2
4th Convolution	28×28; kernel 3×3; ReLU; padding = 'same'
4th MaxPooling	6×6, pooling size: (2×2)
5th Convolution	4×4; kernel 3×3; ReLU; padding = 'same'
5th MaxPooling	6×6; pooling size (2×2)
Dropout	50% of neurons randomly deactivated (rate = 0.5)
Flatten	1456 nodes; activation = ReLU
Dense Layer 1	512 nodes; activation = ReLU
Dense Layer 2	256 nodes; activation = ReLU
Output Layer	10 nodes; activation = Softmax
Loss Function	Categorical Crossentropy
Optimizer	Adam
Learning Rate	0.001

Nowadays, CNN (Convolutional Neural Network) has be- come the standard neural network approach for training and analyzing visual data. This technology utilizes matrix convolution to filter images effectively. A typical CNN architecture consists of several key components, The model comprises several layers: the input layer, convolutional layers, fully connected layers, pooling layers, and dropout layer. These layers are intricately connected to form the CNN, which is ultimately linked to a dataset classification layer for comprehensive data training [22]. Each layer processes the input test set and performs a series of calculations. For a tabular representation of this architecture, refer to Table I.

F. Transfer Learning

In this study, we harnessed the power of transfer learning to enhance the performance of our tomato leaf disease classification model (See Fig. 2). Transfer learning is a machine learning technique where a model trained on one task is adapted for a related task. In our case, we employed three well established pre-trained models: EfficientNetB3, Xception, and MobileNetV2, which were originally trained on vast image datasets such as ImageNet.

- **EfficientNetB3**: We employed EfficientNetB3, a highly efficient and accurate CNN architecture, as the core of our transfer learning strategy. By fine-tuning this model on our tomato leaf disease dataset, we took advantage of its capacity to capture detailed features from the images.
- **Xception:** Xception, recognized for its depth-wise separable convolutions, was another key pre-trained model used in our approach. By tailoring Xception to our specific task and fine-tuning its layers, we utilized its ability to perform hierarchical feature extraction, which is especially effective for intricate image recognition tasks such as disease classification.
- **MobileNetV2:** Developed for mobile and embedded vision applications, MobileNetV2 provided us with a lightweight yet high-performance solution. [34]. We implemented MobileNetV2 on our dataset, leveraging its efficiency and compatibility with the requirements of real-time applications. [35]". Thus, while EfficientNetV2, Swin, and ConvNeXt are promising and in some cases could outperform EfficientNetB3 under identical conditions, the choice of EfficientNetB3 in this work was motivated by its demonstrated accuracy, efficiency, and deployability for agricultural applications. Future extensions of this study may investigate whether Swin or ConvNeXt provide better generalization under domain shift (lab → field images), where transformers are expected to hold an advantage.

G. Saliency Map and Grad-CAM Analysis

In this study, we dive deeper into the interpretability of our tomato leaf disease detection models, aiming to provide insights into their decision-making processes. Two essential techniques, Grad-CAM and Saliency Maps (Gradient-weighted Class Activation Mapping), are employed to enhance the transparency and comprehensibility of our AI-driven system [25, 36].

- **Saliency Maps:** Saliency maps are used to emphasize the regions in an input image that have a substantial impact on the model's classification decision. Visualizing these key regions provides valuable insights into the features of tomato leaf images that our models prioritize when predicting diseases. This transparency helps us understand the model's decision-making process and highlights potential areas for improvement. To assess the importance of a pixel $x(i,j)$, we calculate the maximum of the absolute values across channels. The resulting matrix with dimensions $W \times H$ is referred to as the saliency map [37].

$$SM(i,j) = Max[|G(0,i,j)|, |G(1,i,j)|, |G(2,i,j)|] \quad (1)$$

- **Grad-CAM (Gradient-weighted Class Activation Map-ping):** Grad-CAM takes interpretability a step further by not only highlighting salient regions but also associating them with specific disease classes. This technique provides a more fine-grained understanding of the model's decision process, allowing us to determine which parts of the image contribute most to the classification of a particular disease. Grad-CAM aids in model debugging, validation, and further refinement [38].

The weight $\alpha_k{}^c$ is calculated based on the gradient of the model output y^c with respect to the activation map A_k. for each pixel (i, j) in the activation map A_k. This weight represents the importance of each activation map for class c.

The formula used to calculate $\alpha_k{}^c$ is as follows:

$$\alpha_k{}^c = (1 / Z) \times \Sigma_i \Sigma^j (\partial y^c / \partial A_{ij}{}^k) \quad (2)$$

where: 1) Z is the total number of pixels in the activation map, i.e., $Z = H \times W$, where H and W are the dimensions of the activation map.

2) $\partial y^c / \partial A_{ij}{}^k$ is the gradient of the output for class c with respect to pixel (i, j) in the activation map A_k.

The formula used to calculate the Grad-CAM map is as follows:

$$L^C{}_{Grad\text{-}CAM} = ReLU(\Sigma_k \alpha_k{}^c A_k) \quad (3)$$

IV. Results and Discussion

The global agriculture sector faces significant threats from plant diseases, endangering food security and agricultural productivity. In response to these challenges, our study introduces a model that utilizes deep transfer learning to recognize diseases in tomato leaves. We harnessed the capabilities of Convolutional Neural Networks (CNNs), renowned for their prowess in image recognition tasks. Our investigation encompassed the utilization of pre-trained models, namely EfficientNetB3, Xception, and MobileNetV2, to identify and categorize tomato leaf diseases. Our experimental findings underscore the robust performance of these models, with EfficientNetB3 achieving an impressive accuracy of 0.995, MobileNetV2 at 0.94, Xception at 0.95, and our CNN model at 0.93 (See Figs. 3 and 4). Table II shows the training parameters of performed experiment.

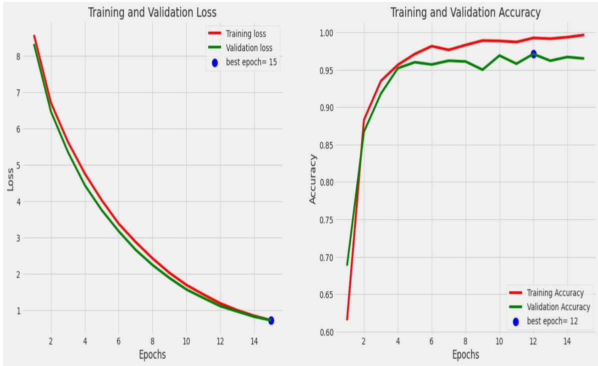

Fig. 3. Graph accuracy and loss curve of EfficientNetB3.

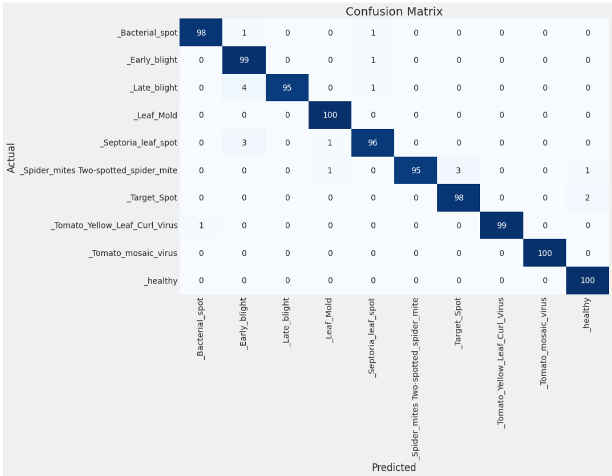

Fig. 4. Confusion matrix of EfficientNetB3.

TABLE II. Overview of the Basic Training Configuration

Models	Training Parameters	Epochs	Optimizer
EfficientNetB3	11,094,346	15	Adam
CNN	184,201	15	Adam
MobileNetV2	12,820	15	Adam
Xception	**1,214,502**	**15**	Adam

However, our contributions extend far beyond achieving high accuracy (See Table III). We have developed an integrated system that seamlessly combines machine learning techniques with advanced image processing methods. This fusion equips the system to promptly diagnose tomato leaf diseases at the onset of symptoms, providing farmers with vital, timely information. This automation empowers farmers to administer precise treatments, effectively managing crop health and mitigating the spread of diseases.

TABLE III. Models Performance (Testing data)

Models	Accuracy	precision	Recall	F1 score
EfficientNetB3	0.995	0.981	0.973	0.975
Xception	0.95	0.923	0.911	0.915
MobileNetV2	0.94	0.914	0.890	0.901
CNN	0.93	0.912	0.88	0.895

Furthermore, our research delves into the realm of model interpretability, employing techniques like Saliency maps and Grad-CAM to illuminate the internal workings of our deep learning models (See Figs. 5 and 6) where Saliency maps and Grad-CAM result are obtained from highest accuracy classifier EfficientNetB3.

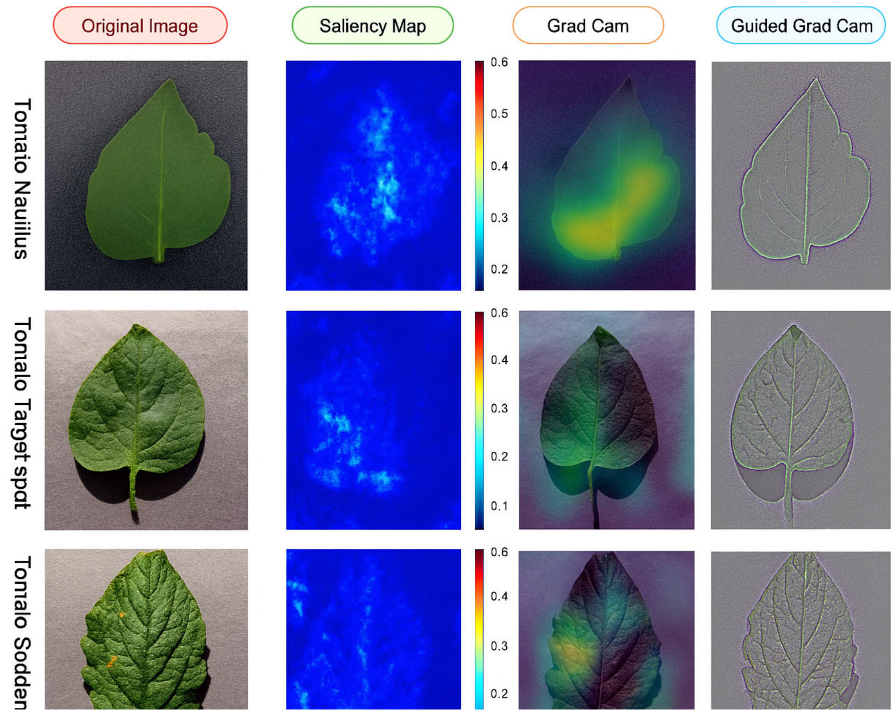

Fig. 5. Saliency map and Grad-CAM analysis(1).

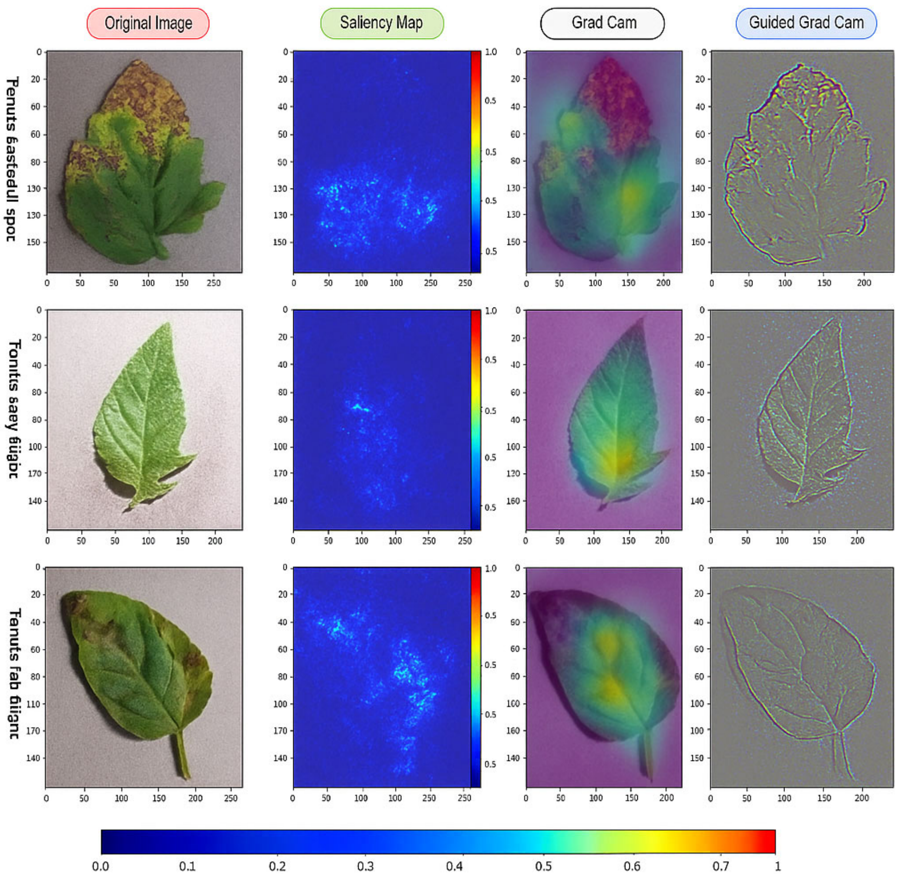

Fig. 6. Saliency map and Grad-CAM analysis(2).

This interpretability not only enhances the transparency of our AI-driven disease detection system but also fosters trust and confidence among end-users, particularly within the agricultural community. Our study signifies a significant step towards the practical application of explainable AI in agriculture, enabling precise and timely disease management to safeguard global food security. In the domain of tomato disease detection, our XAI-based approach competitive results compare to existing methods like.

Author in [38] reported an accuracy of 96.82% but did not incorporate Explainable AI (XAI) techniques. Similarly, Too [18] achieved an accuracy of 97.19%, and Das [24] recorded 95.4%, both without employing XAI. Bhandari [5] reached a notable 99.34% accuracy, also without XAI. In contrast, Smith [21] utilized Grad-CAM and lime (an XAI method) and achieved 99.84% accuracy. Our approach, leveraging both Saliency Maps and Grad-CAM, demonstrated a strong average accuracy of 99.5% (refer to Table IV). These results highlight the effectiveness of our method, which distinctly excels in performance.

TABLE IV. COMPARATIVE PERFORMANCE OF OUR MODEL AGAINST STATE-OF-THE-ART APPROACHES

Reference	Accuracy	XAI
[38]	96.8%	Not Apply
[17]	77.2%	Not Apply
[18]	97.19%	Not Apply
[23]	95.4%	Not Apply
[5]	99.34%	Not Apply
[21]	97.24%	GradCAM and lime
Proposed Method	99.5%	Grad-CAM and Saliency Maps

Accuracy of 99.5%, achieved through the combined use of Saliency Maps and Grad-CAM. This solidifies the notion that integrating XAI techniques, such as Grad-CAM and Saliency Maps, into our approach competitive accuracy compared to others methods that do not incorporate XAI (Saliency maps).

V. LIMITAION

Despite the promising results, this study faces several limitations. First, the reliance on the PlantVillage dataset, which consists of clean and well-illuminated leaf images, raises concerns about the generalization ability of the proposed models to real-world agricultural environments characterized by variable lighting conditions, background noise, and overlapping leaves. Second, the computational complexity of high-performing models such as EfficientNetB3, which requires more than 11 million parameters, may hinder their practical deployment on mobile or embedded devices commonly used by farmers in the field. Finally, while the framework demonstrates strong performance for tomato leaf diseases, its applicability remains limited to this specific crop. The lack of validation on other plants restricts the current system's broader scalability, highlighting the need for further research to extend the approach to diverse agricultural contexts.

V. CONCLUSION

This study presents a deep transfer learning framework for the early detection of tomato leaf diseases, using pre-trained CNN models such as EfficientNetB3, Xception, and MobileNetV2. The method combines image processing and machine learning to enable accurate and timely diagnosis, supporting better crop management. Emphasis is placed on interpretability through visualization techniques like saliency maps and Grad-CAM, fostering transparency and trust. The framework is designed for scalability, with future work aimed at extending its application to other plant diseases and enhancing its robustness through advanced interpretability tools.

This interpretability fosters trust and promotes the practical deployment of AI-based systems in real-world agricultural settings. Future directions for this work include extending the framework to a broader array of plant diseases, thereby increasing its applicability across diverse crops. Furthermore, we aim to advance model transparency by exploring novel interpretability techniques and methodological enhancements, ultimately reinforcing user trust and the system's reliability in agricultural decision-making contexts.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Laatiri Youssef and Mohamed Ali Mahjoub conducted the research, analyzed the data, and wrote the paper; all authors had approved the final version.

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