Efficient Mulberry Leaf Disease Detection in Bangladesh: A Lightweight Approach for Real-Time Applications

Ananta Raha
Department of Computer Science and Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
ananta.raha.99@gmail.com

Quazi Samiha Tasnim
Department of Computer Science and Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
quazisamiha@gmail.com

Abstract*—Bombyx mori, the silkworm species that feeds on mulberry leaves, produces the most prevalent variant of silk worldwide. Unfortunately, mulberry trees suffer from leaf diseases that spread quickly and cause significant losses in production. Identifying diseases by experts on large scale is time-consuming and often inaccessible for rural people. Despite recent advances in deep learning and image processing, State-of-the-art models tend to be computationally expensive and must be used online. This study makes use of a regional dataset that comprises of mulberry leaf images captured from Rajshahi, the principal sericulture region in Bangladesh, to align with the environmental factors of the country. Firstly, we present an extremely efficient and lightweight approach enhancing a pre-trained MobileNetV2 model to classify among three categories of leaf photos: disease free, leaf spot, and leaf rust. Upon comparison with base MobileNetV2 and existing works on this dataset, this model exhibited efficacy in accuracy, recall, precision, and F1-score, attaining remarkable values of 98.63%, 98.53%, 98.63%, and 98.63%, respectively after 5-fold cross-validation. Then, we performed an explainability analysis utilizing Grad-CAM visualization to validate the capability of our suggested method. We also assessed the impact of preprocessing techniques on classification outcomes. The proposed architecture, having only 145K parameters, remains surprisingly lightweight and outperforms the base MobileNetV2 model in our experiments. According to the results, our suggested approach correctly identifies mulberry leaf diseases, supporting sericulture growth in rural areas.

***Index Terms*—mulberry leaf, classification, lightweight, explainable, deep learning, MobileNetV2, Squeeze-and-Excitation, CNN**

I. Introduction

Silk is a structural protein generated, released, and transformed into thread by numerous arthropods for external use outside of their body [1]. Traditionally, textile silk is produced using a kind of mulberry silkworm called *Bombyx mori*, prevalent in China that was domesticated from its native ancestor, *Bombyx mandarina* [2]. Evolved in China from *B. mandarina* around 4600 years back, *B. mori* silkworm lives on mulberry leaves [3]. The mulberry tree, scientifically known as *Morus alba*, is a deciduous plant native to northern China that has been farmed for generations all over the world [4]. Mulberry trees continue to be commercially and environmentally important due to their numerous applications. Mulberries are edible fruits that can be eaten raw or transformed into a variety of items, including juices, jams, and wines. Besides, it is a nutrient powerhouse consisting of vitamins, minerals, and bioactive phenolic chemicals with antioxidant properties. [5], [6]

A commonly used term related to silk goods is Sericulture, which refers to the extensive process of cultivating mulberry trees, nourishing silkworms by feeding leaves, maintaining and harvesting of the cocoons they form, and transforming them into textile silk [7]. During this procedure, diverse clinically significant byproducts get produced, that illustrates the wide array of silkworm applications [8]. Sericulture is significant not only economically, but also culturally, historically, and ecologically in many civilizations around the globe. Millions of people rely on the silk industry for their livelihood. Historically, Silk manufacturing is believed to have originated in ancient China around 2700 BCE [7].

The sericulture industry in Bangladesh, as a prospective earning sector, holds a tremendous potential to create livelihoods and eliminate unemployment for a large number of the country's population, particularly in rural regions. This industry has plenty of room to grow if it receives the right attention and assistance from the government and non-governmental groups. However, it is currently battling to exist due to issues such as capital, infrastructure, mulberry diseases, limited access to newer technologies, marketing challenges, and so on. The majority of these problems can be remedied by properly raising silkworms. However, it requires the stable and effortless cultivation of mulberry plants, since their leaves serve as the only food source of silkworm *Bombyx mori*. [9].

Despite growing year-round, mulberry leaves are prone to diseases caused by various microorganisms, as well as serious pests including sap suckers and defoliators. These issues cause a 12-25% reduction in leaf production [10]. Besides, leaf spot, powdery mildew, and rust are fungal diseases that can reduce the nutrient composition of the leaves. Supplying these lower-quality leaves creates a negative impact on silkworm growth and, eventually, the silk manufacturing business. It is unfortunate that rural farmers in under-developed countries like Bangladesh cannot afford to have these diseases detected manually, especially in large fields. Considering these factors, the use of automated, reliable and accessible disease detection systems is crucial, since they can increase the rate of mulberry production and, in turn, benefit the silk industry.

Deep learning, a contemporary subdomain of machine learning, has become a potent instrument for image processing and object detection systems. Attaining success in other domains, it has lately entered the agricultural sector, allowing for the quick identification of diseases in crops like maize, rice, etc. However, deep learning approaches for mulberry disease detection are still remained under-explored, mostly owing to the absence of publicly accessible datasets. The Mulberry Leaf Dataset [11], [12], which includes leaf photos from the Rajshahi region of Bangladesh, fills this void by providing a resource that is consistent with local ecological conditions. Most of the existing approaches, however, require large computational resources to reach an acceptable performance, which makes practical deployment difficult. To mitigate these issues, the following key contributions have been made in this paper:

1) An extremely lightweight and efficient multiclass classifier was developed by altering pretrained MobileNetV2 to identify leaf spot, leaf rust, and disease-free leaves.
2) Performance and complexity was compared to baseline MobileNetV2 and other existing techniques to demonstrate the effectiveness of our proposed architecture.
3) Grad-CAM visualization was utilized in order to verify model predictions and ensure explainability.
4) The impact of a preprocessing technique on the Mulberry Leaf Dataset [11], [12] was assessed alongside.

Section II explores contemporary research works in this field, covering the principal aspects of this study. An in-depth description of the proposed approach has been presented in Section III. Section IV breaks down the description and analysis of dataset, results derived from the experiments, and performance comparison with existing works. Section V contains discussion and potential scope of future improvements.

II. Related Works

Researchers have been leading the way in developing advanced techniques for automatically diagnosing and categorizing plant diseases in the field of plant pathology. Recent studies have shown the feasibility of using CNN to accurately detect plant diseases from leaf images. For example, Eunice et al. performed efficient plant disease identification on popular PlantVillage dataset [13] by fine tuning renowned pretrained models VGG-16, InceptionV4, ResNet-50, and DenseNet-121 [14]. A series of research work was carried out on disease recognition in tomato leaves. The work of Prajwala et al. [15], Huang et al. [16], Agarwal et al. [17], Hailin et al. [18] are noteworthy. For similar task, a CNN model built on Residual Attention was applied after preprocessing with a type of Retinex technique, which achieved about 89% accuracy on a dataset of 8616 images [19]. Among other crops, maize disease classification has gained the attention of a lot of researchers [20]–[22]. An array of supervised techniques including SVM, Decision Tree, KNN, Naive Bayes, Random Forest were applied in the work of Panigrahi et al. for maize plant disease detection, among which the Random Forest approach yielded the highest accuracy of 79.23% [23]. Another notable work based on Faster R-CNN was done for accurate maize leaf disease detection, that achieved an accuracy of 97.23% [24]. Among other crops, apple, orange, rice have grabbed the attention of scholars, which is evident in several works based on CNN [25]–[29]. However, there are only a limited number of studies on deep learning based mulberry leaf diseases. One of the major reason behind this is the lack of sufficient datasets. A noteworthy work on mulberry leaf diseases has been done by Salam et al., in which they collected a set of 1,091 mulberry leaves from the north-western part of Bangladesh. They proposed a lightweight model based on MobileNetV3, which achieved a maximum accuracy of 96.4% [12]. In another earlier work, they have presented an explainable approach for accurate detection of mulberry leaf diseases, which substantially reduced the trainable parameters and complexity of the model [11]. After reviewing all this works, there is a high need for developing a more robust, lightweight, yet efficient mulberry disease detection approach that is applicable in low-powered devices, in order for working offline, which is necessary for remote people in underdeveloped countries like Bangladesh. By advanced preprocessing techniques, the existing pretrained models can be further optimized to fulfill our goals. Among preprocessing techniques, Retinex-based image enhancement is quite popular. Retinex theory was first introduced by Edwin H. Land and John J. McCann in 1971 [30]. The Retinex technique enhances digital image quality by mimicking the human visual system's capability of perceiving color and details under varying lighting conditions. The Multiscale Retinex (MSR) approach is an extension which is especially useful for low-light or high-contrast images, making them visually more natural and informative [31]. In our work, we have utilized the Squeeze-and-Excitation (SE) module [32] to enhance a pretrained MobileNetV2 model. The SE module re-weights feature map channels by incorporating Global Average Pooling (squeeze) and a lightweight fully-connected network (excitation) to learn channel-wise weights, emphasizing important features. It helps to reduce trainable weights with a minimal footprint. Besides, we assessed how the precision changes after applying a popular preprocessing technique called MSRCR (Multi-Scale Retinex with Color Restoration), which is an extention of MSR [33].

III. Methodology

The proposed architecture contains a Modified MobileNetV2 that also integrates a Squeeze-and-Excitation (SE) module at the last stage of the feature extractor. Subsequent portions provide a comprehensive description of these components.

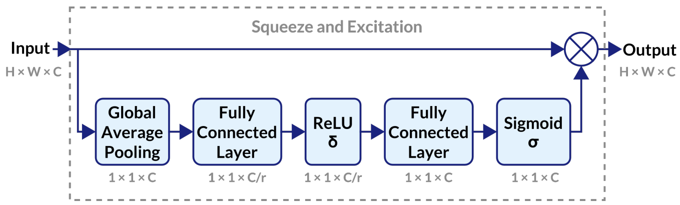

Fig. 1: Block diagram of SE module [32]

A. *Squeeze-and-Excitation Module*

The SE module has been adopted directly from the work of Jie Hu et al. [32]. It improves a network by automatically calibrating channel-wise features. It creates a global context by ”squeezing” spatial dimensions and the ”excitation” part reweights channels according to their importance. Fig. 1 illustrates the block diagram of the SE module. If SE input is $\mathbf{x} = [x_1, x_2, ..., x_c]$, where x_i represents the features of i^{th} channel having spatial dimensions $H \times W$, then spatial information is at first squeezed into **z** by using global average pooling, where c^{th} channel output, z_c is given by (1).

$$z_c = F_{sq}\left(x_c\right) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} x_c\left(i, j\right), \tag{1}$$

$$\mathbf{p} = F_{ex}\left(\mathbf{z}\right) = \sigma\left(\mathbf{w}^{''} \delta\left(\mathbf{w}^{'}\mathbf{z} + \mathbf{b}^{'}\right) + \mathbf{b}^{''}\right), \tag{2}$$

(3)

In the excitation part, if $\mathbf{w}^{'}, \mathbf{b}^{'}$ and $\mathbf{w}^{''}, \mathbf{b}^{''}$ denotes the weights and biases for the two fully-connected layers, then excitation output should be **p**, as given by (2). Here, σ, δ denote sigmoid and ReLU functions, respectively. Finally as in Equation 4, the SE output, **se** is the channel-wise multiplication of **x** and **p**. [32]

$$SE_c\left(x_c\right) = p_c \cdot x_c \tag{4}$$

B. *Modified MobileNetV2 Architecture*

The original MobileNetV2 in [34] has been chosen because of its efficient classification performance and relatively small complexity. Its key element is an inverted residual structure, which utilizes pointwise and depthwise separable convolutions.

Fig. 2 highlights our proposed modifications. We used a TensorFlow implementation which was pretrained with ImageNet weights. It greatly benefits the new architecture since the diverse feature extraction capability is replicated. However, to further reduce the complexity, subsequent stages after 7^{th} bottleneck block (and ReLU) were eliminated. This change was the outcome of our numerous experiments for simplifying the model. To compensate for this alteration, an SE module was attached, followed by a GAP layer to properly weight its feature channels. Because of the existing pair of fully-connected (FC) layers in the SE module, no further FC layers were introduced other than the final output layer, which consisted of three units for our particular classification purpose. Here, softmax activation was applied for producing probability vectors.

$$H(y, \hat{y}) = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{5}$$

The loss function utilized in the proposed model was categorical cross entropy which can be represented by (5) where, y_i and $\hat{y}_i$ are the true and predicted probability distribution for class i.

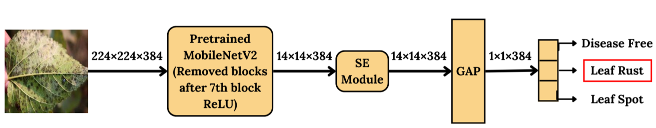

Fig. 2: Classification using proposed modified MobileNetV2 architecture

IV. Results & Discussion

A. *Description of Dataset*

The Mulberry Leaf dataset [11], [12] comprises 1,091 mulberry leaf photos captured using a camera in natural lighting conditions from mulberry fields in Rajshahi, Bangladesh. There are 440 normal, 489 leaf rust, and 162 leaf spot photos. Each photo having a resolution of 4,000×6,000 pixels was annotated by a sericulture expert in collaboration with the Bangladesh Sericulture Development Board (BSDB). Fig. 3 shows some samples taken from each class. The photos have uneven lighting, and some leaves have shadow. At the first glance, it is hard to distinguish between Leaf Spot and Leaf Rust photos.

The sample distribution in the dataset is illustrated in Fig. 4, which exhibits a strong class imbalance. Due to the limited

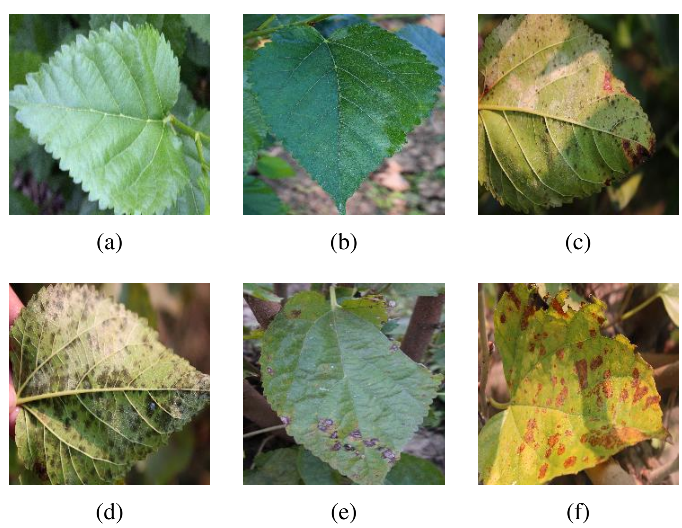

Fig. 3: Samples from dataset; (a-b) Disease Free, (c-d) Leaf Rust, (e-f) Leaf Spot

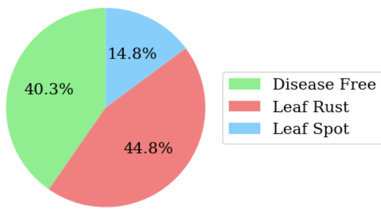

Fig. 4: Class distribution in dataset

number of Leaf Spot photos, data augmentation became necessary. During cross-validation, we augmented images for each class from the training splits, in order to make the training size to around 7500, and thus mitigating the class imbalance problem. Random horizontal flip, and rotation by 90°, 180°, and 270° are were applied, along with random brightness variation up to 10%.

B. Preprocessing Techniques

Effective preprocessing is critical for maximizing the efficacy of deep learning models, particularly in datasets containing inherent noise. We applied minimal image enhancements for assessing the effect after model training. In our experiments, MSR (Multi Scale Retinex) was used to regulate the dynamic range, along with color restoration. A channel-wise gamma transformation was then applied as an improvement. Following the aforementioned procedures, the photos have consistent color and detail, even in shadowy and dark regions. Fig. 5 shows examples of both untouched and preprocessed photos.

C. Experimental Setup

All the tests were done on Kaggle using a machine with an NVIDIA P100 GPU and 16 GB of GPU memory. TensorFlow, Keras, and other similar packages were used extensively to make the training and testing process straightforward to run. Table I shows the exact setup that was used to train the models. Adam (Adaptive Moment Estimation) optimizer was employed due to its faster convergence. For evaluating the proposed model, we made use multiple metrics, namely, Precision, Accuracy, Recall, and F1 Score, defined by equations (6)-(9).

TABLE I: Training configuration

Parameter	Value
Optimizer	Adam
Learning rate	0.00001
Batch size	64
Epoch	80

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{6}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{7}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{8}$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

D. Comparison of results

The images were resized to 224×224 for ensuring compatibility with the models. We employed five-fold stratified cross-validation technique, and evaluated the performance of our modified architecture and the base MobileNetV2 model. Fig. 6 illustrates the transition of loss in addition to accuracy during the training process. The base MobileNetV2, after 40 epochs, started to overfit and its validation loss started to increase. Begining with a lower value of nearly 0.7, its validation accuracy remained quite consistent after 30^{th} epoch.

Table II presents a side-by-side comparison of the test results. Surprisingly, preprocessing approaches had barely any impact on both of the architectures. One probable explanation might be that majority of the dataset photos already have adequate detail and contrast for feature extraction. Fig. 7

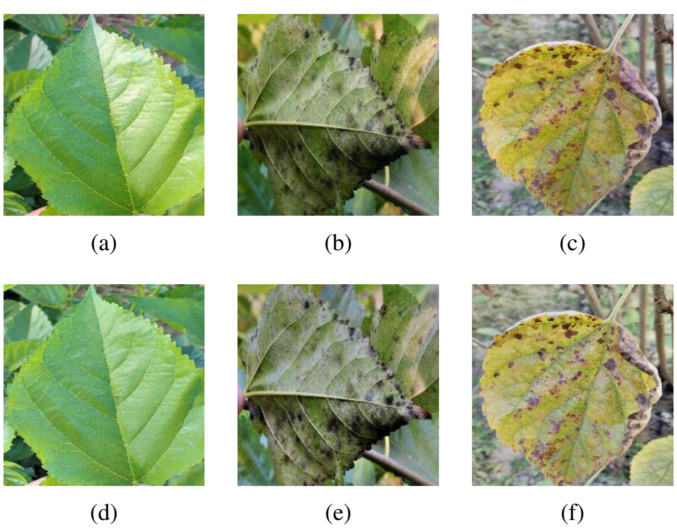

Fig. 5: (a-c) No preprocessing; (d-f) MSRCR enhanced

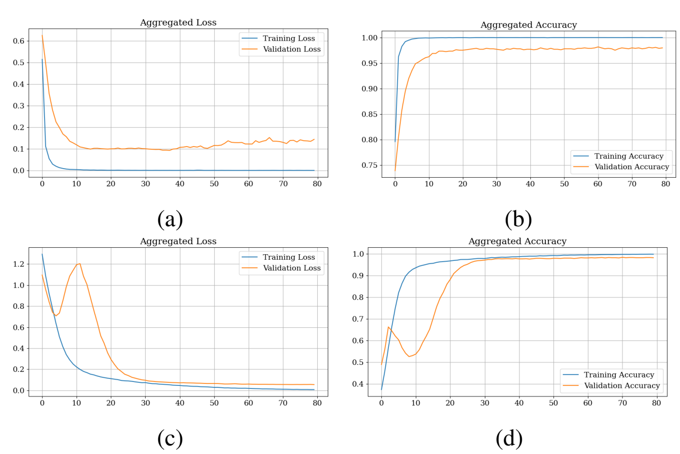

Fig. 6: Loss and accuracy curves for (a-b) MobileNetV2 and (c-d) Proposed method

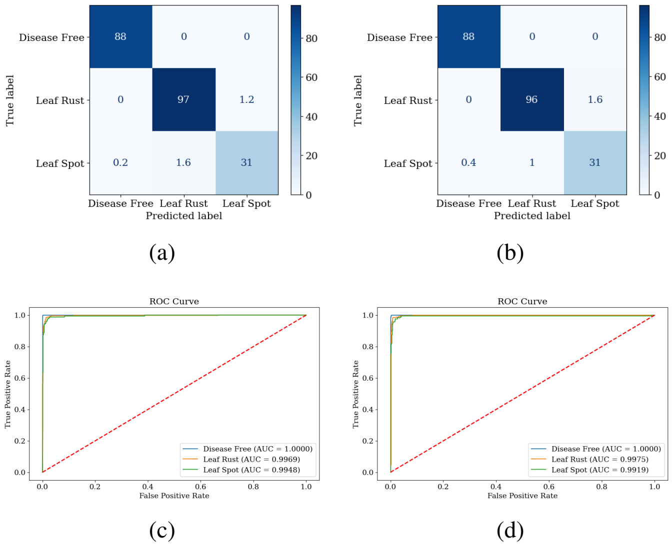

Fig. 7: Aggregated confusion matrix for (a) MobileNetV2, (b) Proposed modified model; ROC curves for (c) MobileNetV2, (d) Proposed modified model

depicts the mean confusion matrices and ROC curves for comparison. Our proposed method gave comparable scores with the baseline MobileNetV2, especially for Leaf Rust. After all, it is evident from the results that our proposed architecture matches the base MobileNetV2 model in terms of all performance metrics.

TABLE II: Comparison of cross-validation results between proposed method and base MobileNetV2

Metric Name	**No preprocessing**		**Preprocessed**	
	MobileNetV2	***Proposed***	***MobileNetV2***	***Proposed***
Accuracy	**98.63**	**98.63**	98.53	**98.63**
Precision	**98.63**	**98.63**	98.53	98.62
Recall	**98.53**	**98.53**	98.44	98.35
F1 Score	**98.63**	**98.63**	98.53	**98.63**

When comparing computational complexity to existing studies, our model ranks first, as shown in Table III. The closest performance was obtained by PDS-CNN [11]. Our updated model surpasses their scores on this dataset, but has a trainable parameter count of around half of the nearest work [12].

TABLE III: Result comparison with existing works

Method	**Accuracy** (%)	**Precision** (%)	**Recall** (%)	**F1** (%)	**Param.** (million)
PDS-CNN [11]	95.05	93.20	92.80	93.00	0.53
Salam et al. [12]	96.40	97.00	96.40	96.40	0.30
Proposed	**98.63**	**98.63**	**98.53**	**98.63**	**0.14**

E. Grad-CAM Visualization

The Grad-CAM outputs for all three classes are presented in Fig. 8. It is apparent from the generated activation heatmaps that our method focuses more on the affected area of the leaves during classification.

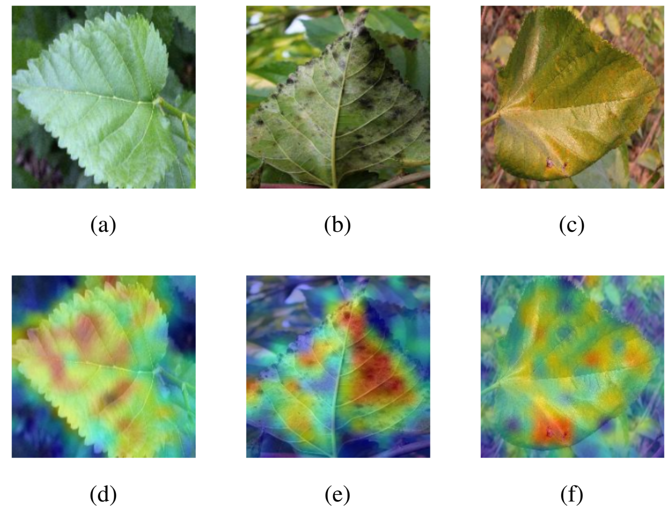

Fig. 8: Grad-CAM visualization for proposed method (a-c) Input images and (d-f) Generated heatmaps

V. Conclusion

An extremely lightweight model for mulberry leaf disease detection was proposed in this study. For enhancement, a pretrained MobileNetV2 model was altered and SE module was integrated. After comparing the experimental results with the base MobileNetV2 model, our method showed superior scores in all the considered metrics. With a tiny file size of 568.45 kilobytes and small parameter count of 145,523 our suggested architecture fulfills the key objectives, and proved to fill the gap of a very low-complex, efficient detection method for mulberry leaf diseases. The lightweight nature should definitely help the remote farmers to boost their mulberry cultivation. Besides, a popular preprocessing technique was applied on the dataset for assessment, which yields in minimal alteration in classification performance. Future scopes include actual mobile implementation, and applying the proposed architecture on other crop datasets in order to further evaluate its generalization capability.

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