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A YOLOV8 CLASSIFICATION APPROACH USING ESPCN PROCESSED IMAGES FOR BEAN LEAF DISEASE DETECTION

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ABSTRACT

Agriculture is crucial for economic growth, with automation emerging as a global concern due to the increasing population and food demand. Beyond simple cultivation, agriculture is vital to communities, the foundation of economies, and the first line of defence against the threat of food insecurity. Plant diseases pose a constant threat to this vital industry, while they also present several other difficulties. Plant diseases also pose a threat to crop productivity and the fragile balance that exists between food production and the growing needs of an expanding world population. Beans are a vital crop that has served mankind as a nutritious crop throughout history. This research work has classified bean leaf diseases of angular leaf spot, bean rust, and healthy bean leaves using Artificial Intelligence fused technologies. While testing on preprocessing methods, image-enhancing algorithms such as Fast super resolution Convolutional Neural Networks (FSRCNN), Efficient Sub-Pixel Convolutional Neural Networks (ESPCN), and Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) were used to boost image quality in the respective training phases. Out of the pre-trained Convolutional Neural Networks (CNN) such as MobileNet, MobileNetV2, EfficientNetB0 - B6 models, NasNet, and You Only Look Once - Version 8 (YOLOv8) model, the YOLOv8 model gave an impressive model accuracy of 99.6% when the images were enhanced using ESPCN algorithm while classifying the images accurately. YOLOv8 proved the best model performance by scoring optimal metric values compared to CNN models. Therefore, it can be concluded that YOLOv8 with ESPCN can be used to efficiently classify bean leaf diseases and achieve promising results.

KEYWORDS: *Bean leaf diseases, ESPCN, Multi-class classification, YOLOv8*

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1. INTRODUCTION

In recent years, the balance between global food production and demand which determines global food security has grown in importance on the international (Qazi and Al-Mhdawi, 2025; Thomas *et al.*, 2025; Tkemaladze, 2025). Food price increases that happened in 2008 sparked a huge global crisis that led to political and economic unrest in some developing nations that have continued till the current timeline (Thomas *et al.*, 2025). According to estimates, the ongoing expansion in the human population will result in a 40 year increase in the demand for food. Forecasts indicate that by 2050, 70% more food will need to be produced to meet demand (Caubel *et al.*, 2017). Therefore, it is becoming more and more important to practice sustainable and effective crop cultivation given these growing threats to global food security. As the foundation of our food production system, crop agriculture has proven to be a critical answer to the growing needs anticipated in the ensuing decades (Caubel *et al.*, 2017).

Considering the agricultural system's critical importance, it is necessary to put measures in place that protect its resilience and integrity. This means putting strategic plans into action to support the agriculture industry and make sure it remains productive and flexible enough to meet changing needs. Taking into account risks in the agricultural sector, crop pests and diseases are hugely responsible for direct yield losses ranging between 20% and 40% of global agricultural productivity and regularly threaten global food security (Martinelli *et al.*, 2015). However, crop losses remain poorly recognized as an important driver in matters of food security, whereas plant diseases have had an enormous impact on livelihoods throughout human history (Martinelli *et al.*, 2015). To stop the spread of disease and make effective management techniques easier, it is crucial to monitor plant health and identify pathogens early on (Javaid *et al.*, 2023).

Globally, another primary issue and a concerning topic is the automation of agriculture. Since the population is growing at an exponential rate, it has driven up demand for jobs and food simultaneously. For the farmers to meet these needs, the traditional techniques they employ are no longer sufficient. Stricter laws, a decline in the number of farms, a labor shortage, and a rising global population also have driven farmers to look for new solutions (Martinelli *et al.*, 2015).

In the current world, nearly every industry is impacted by the introduction of technologies such as the Internet of Things (IoT), Big Data and analytics, Artificial Intelligence (AI), and Machine Learning (ML) (Javaid *et al.*, 2023). Disease detection hence be automated with deep learning models, doing away with the requirement for manual inspection (Javaid *et al.*, 2023). This can greatly boost productivity, particularly in large agricultural areas where labor and time intensive human inspection can be necessary (Talaviya *et al.*, 2020). Early disease detection is also possible using deep learning models, frequently before symptoms become apparent to the unaided eye. Such early diagnosis will allow for timely management, preventing the spread of illnesses and minimizing crop losses (Talaviya *et al.*, 2020). This is essential for keeping crops in their best condition and managing diseases effectively. Another concern is that biased opinions could exist in manual processes since different persons may interpret symptoms differently. Deep learning methods can reduce the variability associated with human judgment by offering an unbiased and standardized approach to disease identification (Javaid *et al.*, 2023), .

Thus, in the classification of leaf diseases as a popular crop, beans have been the main emphasis of this research. Beans are a long-standing plant that has provided numerous advantages to humans over time. A bean is the seed of a variety of plants in the Fabaceae family that are consumed by humans and animals as vegetables (Gepts and Debouck, 1991). Throughout history, beans have been a vital source of protein. Numerous bean varieties, such as kidney beans, are rich in anti-nutrients, which are natural or synthetic compounds that interfere with the absorption of nutrients that impede the body's use of certain enzymes (Creese, Ad and Mellanby, 1939). Phytic acid and phytates, found in grains, seeds, nuts, and beans, disrupt the metabolism of vitamin D and impede bone formation (Creese, Ad and Mellanby, 1939). Thus, the bean crop stands as an agricultural commodity of considerable importance.

This research work has therefore focused on classifying two bean leaf diseases and healthy bean leaves by using several image-enhancing algorithms to increase the image quality of the dataset while Convolutional Neural Networks (CNN) and the recently introduced You Only Look Once - Version 8 (YOLOv8) model to train the data models to determine which classification model is optimal in classifying the bean leaf diseases. The research questions were aimed to find how ESPCN image enhancement affect YOLOv8's classification accuracy on bean leaf lesions and as well as to investigate how ESPCN enhanced YOLOv8 model perform against baseline CNN models.

While YOLO models, such as YOLOv8 have been recognized for their effectiveness in plant disease detection (Rodriguez-Lira *et al.*, 2024), it can be further focused on to perform an investigation on how specific image super resolution techniques such as ESPCN can further enhance YOLOv8's classification accuracy and efficiency for bean leaf diseases detection. Moreover, a comparative performance analysis between the enhanced YOLOv8 fused ESPCN framework and conventional CNN architectures would provide valuable insights for the research community by establishing clear performance benchmarks across different model combinations.

This study is organized as follows: section III describes the methodology that was been carried out, and section II covers the literature review on similar work. Section V offers the study's conclusion, and section IV summarizes the results.

Related Work

Singh, Chug, and Singh (2022) have used a dataset of 1295 bean leaf images that consisted of three different classes. The dataset therefore consisted of bean leaf disease images of angular leaf spot disease, bean rust disease, and as well as of healthy bean leaves. The authors have tested using pre-trained CNN models such as MobileNetV2, EfficientNetB6, and NasNet models. The best model has been EfficientNetB6 which had a model accuracy of 91.74% (Singh, Chug and Singh, 2022).

Elfatimi, Eryigit, and L. Elfatimi (2022) have conducted a research study using a similar dataset to the dataset used in the research done by (Singh, Chug and Singh, 2022). The dataset used by the researchers has been consisted by 1296 images with images for data classes of, angular leaf spot disease, bean rust disease, and healthy bean leaves (Elfatimi, Eryigit and Elfatimi, 2022). In order to determine which architecture would work best for classifying bean leaf diseases, the researchers compared and evaluated the efficacy of several designs. This allowed them to arrive at a very satisfactory classification result, with the MobileNet model having the classification average accuracy of the proposed model more than 97% on training dataset and more than 92% on test data for the two unhealthy classes and the healthy class.

Imanulloh et al. (2023) have created CNN model for the identification of plant diseases. The suggested CNN model is lightweight and simple enough to be used in model applications. The twelve CNN layers of the suggested CNN model are divided into eight layers for feature extraction and four layers for classifiers. Based on the experimental findings of a dataset on plant diseases that included 87867 picture records across 38 classes, accuracy, precision, recall, and f1-score have been recorded with 97%, 98%, 97%, and 97%, respectively, suggesting the model can achieve good performance without overfitting (Imanulloh, Muslikh and Setiadi, 2023).

In order to classify bean leaf illnesses, the study done by Mehta, Kukreja, and Gupta (2023) presented a CNN technique based on federated learning. By enabling users to train local models on their own datasets without disclosing raw data, the research upholds data privacy. Using an approach developed by the authors, a high-performing global model capable of classifying bean leaf illnesses into five groups was created by combining local models from four customers. The results have shown that each customer's local models did well in terms of accuracy, precision, recall, and F1 score. The weighted, macro, and micro averages of the performance measures have demonstrated that the aggregated global model functioned consistently well for every consumer. The weighted average precision, recall, F1-score, and accuracy of the global model have been 92.61%, 89.72%, and 92.87%, respectively (Mehta, Kukreja and Gupta, 2023).

Through the use of the EfficientNetB0 architecture and Contrast Limited Adaptive Histogram Equalization (CLAHE) method, the study done by Noviandy (2023) has increased the accuracy of bean leaf disease classification. Generalization of the class activation mapping (Grad-CAM), an explainable AI technique, has been used to assess the interpretability and transparency of anticipated images. The accuracy, precision, recall, and F1 score of the suggested method are higher than those of models trained on the original images. For plant disease diagnosis, CNN-based models have been shown to be effectively optimized using CLAHE. GradCAM research demonstrated that the model's emphasis on characteristics associated with the disease improved comprehension of its behaviour. Farmers and other agricultural professionals may now make better decisions thanks to the development of reliable automated technologies for plant disease diagnosis made possible by this research (Noviandy *et al.*, 2023).

The authors of the research work done by Karuna et al (2023) developed a deep learning model that identified several plant illnesses with an impressive 98.82% accuracy rate. The "PlantVillage" Kaggle repository has been used as the dataset. The dataset includes 21000 photos of 15 different disease groups as well as three distinct kinds of tomatoes, potatoes, and bell peppers as data classes (Karuna *et al.*, 2023). Four deep-learning CNN techniques that were VGG16, VGG19, DenseNet201, and GoogleNet (InceptionV1) have been utilized to diagnose plant illnesses. The DenseNett201 model has demonstrated the highest level of accuracy, 98.82% across all data classification scenarios.

Considering the existing literature work, it was identified that research is open to be conducted outside the area of CNN models usage with YOLOv8 classification model. Our study has hence investigated the effectiveness of image-enhancement algorithms in boosting classification performance while identifying a computationally efficient and highly accurate model suitable for real-world agricultural applications.

2. METHODOLOGY

2.1 Dataset Details

The dataset that was used in this study was found in the online repository (*Bean Leaf Lesions Classification*, 2023). The training folder consisted of 1034 images while the testing folder had 133 images of three different bean lesion leaf types, healthy leaves, angular leaf spot, and bean rust. Figure 1 shows a bean leaf that has been detected with angular leaf spot, which is a devastating disease of beans caused by the fungus Phaeoisariopsis griseola (Kaplan, 2008). This disease develops rapidly in warm temperatures, about 25 degrees centigrade but can also occur over a range of moderate to warm temperatures of approximately 16-28 degrees centigrade, when accompanied by wet weather or high humidity alternating with dry, windy conditions (Kaplan, 2008).

Figure 1: A bean leaf detected with angular leaf spot.

Figure 2: A bean leaf detected with bean rust.

Figure 3: A healthy bean leaf.

Figure 2 depicts a bean leaf affected by bean rust that is induced by the fungus, Uromyces appendiculatus (Kaplan, 2008). However, bean rust only rarely develops itself and becomes significant during continuous warm, humid weather. Finally, a healthy bean leaf has been illustrated in figure 3 of a healthy bean crop.

2.2 Image Upsampling

Considering the image quality of the dataset, the algorithms discussed in this section were carried out throughout the image upsampling phase. When compared to interpolation techniques, super resolution offers numerous benefits, including enhanced image clarity and quality, especially for finer textures, edges, and contours (Shi *et al.*, 2016). Additionally, it can lessen noise and artifacts brought on by scaling, compression, or image deterioration (Dong, Loy and Tang, 2016). Higher resolution image analysis and identification, such as face recognition, medical imaging, or satellite photography, can also be made possible by it. Super resolution can also improve an image's realism and aesthetic appeal for use in entertainment, gaming, or the arts.

2.2.1 Using Original Resolution Images

As the first method, the images were used in the original resolution not applying any other operations that would alter the image quality.

2.2.2 Using Image Super-Resolution Methods to Upsample Images

a) Efficient Sub-Pixel Convolutional Neural Network (ESPCN) to Upsample Images: At this stage, Efficient Sub-Pixel Convolutional Neural Network (ESPCN) was used to train the images during upsampling. ESPCN introduced by Shi et al. Shi et al. (2016) has been defined as the first CNN with real-time 1080p video super resolution (SR) trained on a single K2 Graphical Processing Unit (K2 GPU). Hence, Shi et al. retrieved feature maps in the low resolution itself and used complicated upscaling filters to obtain the outcome, as opposed to doing super resolution after upscaling the low resolution using a bicubic filter. The only place the upscaling layers are installed is at the network's end. This makes it quick, especially when compared to other methods, by guaranteeing that the intricate activities taking place in the model occur on smaller dimensions (Shi *et al.*, 2016) .

b) Fast super-resolution Convolutional Neural Networks (FSRCNN)

Dong et al. (2016) presented fast super-resolution Convolutional Neural Networks (FSRCNN) to speed up the previously suggested SRCNN. By adding a deconvolution layer at the network's end, FSRCNN, in contrast to SRCNN, may learn the mapping from the original lower resolution image to the higher resolution image directly. Conceptually, ESPCN and FSRCNN are extremely similar. Both of them use upscaling layers at the end for speed rather than interpolating it early on, and their base structures are modelled after SRCNN (Dong, Loy and Tang, 2016) .

c) Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN)

A groundbreaking invention, the Super-Resolution Generative Adversarial Network (SRGAN) proved to produce realistic textures while applying super-resolution on a single image (Wang *et al.*, 2018). However, Wang et al. (2018) have carefully examined the three main SRGAN components—network design, adversarial loss, and perceptual loss—and upgraded each one to produce an Enhanced SRGAN (ESRGAN) to further increase the visual quality. Compared to SRGAN, the proposed ESRGAN can continuously produce images with higher visual quality and more realistic and organic textures.

2.3. Training the Image Data Using Pre-trained Convolutional Neural Network (CNN) Models

Convolutional Neural Networks (CNN) models are designated models used specially for images based tasks (Li *et al.*, 2022). The CNN is a kind of feed forward neural network that can extract features from data with convolution structures (Li *et al.*, 2022). The application of CNN-based computer vision has facilitated accomplishments that were once deemed unattainable in previous generations. The following CNN models were used to train the image data models in this study.

a) MobileNet

MobileNet introduced by Howard et al. (2017) is based on a streamlined architecture that uses depth-wise separable convolutions to build lightweight deep neural networks (Howard *et al.*, 2017).

b) MobileNetV2

Sandler et al. (2018) discovered MobileNetV2, a model that enhances the state-of-the-art performance of mobile models on numerous tasks and benchmarks as well as across a spectrum of different model sizes (Sandler *et al.*, 2018).

c) Neural Search Architecture (NasNet)

The NasNet model was introduced by Google Brain. The authors, Zoph et al. (2017) suggested using a small dataset to find architectural building blocks and then transferring those blocks to a larger dataset. The NasNet model reduces model size and complexity (FLOPs) while achieving cutting-edge outcomes (Zoph *et al.*, 2017).

d) EfficientNetB0-B6

By scaling up MobileNets and ResNet models, (Tan and Le, 2019) developed the EfficientNet model family, a CNN model family. In this study, model training was done using the extensions of the EfficientNetB0 model, EfficientNetB1, EfficientNetB2, EfficientNetB3, EfficientNetB4, EfficientNetB5, and the EfficientNetB6 model (Tan and Le, 2019) .

An image size of 256 was fed to the CNN models during training considering the computational costs. Using 50 epochs with the Adam optimizer the model training was carried out.

2.4 Training the Image Data using You Look Only Once – Version 8 (YOLOv8)

You Look Only Once – Version 8 (YOLOv8) (Redmon *et al.*, 2016) which was introduced in 2023 was used as the next classification model to train the data model. The Ultralytics YOLOv8 is a state-of-the-art (SOTA) model that has added new features and enhancements to further increase performance and versatility while building upon the success of earlier YOLO versions (Redmon *et al.*, 2016). Because of its quick, precise, and user-friendly architecture, YOLOv8 makes a great option for a variety of applications such as object recognition and tracking, instance segmentation, image categorization, and posture estimation (Redmon *et al.*, 2016).

The YOLOv8n-cls model was hence used as the classification model which was trained for 50 epochs considering an image size of 512 along with a batch size of 16 and a learning rate of 0.00001. Since the YOLOv8 model requires data to be stored in a designated format that should consist of training, testing, and validation sets separately, the images were split into a ratio of 80:10:10 to satisfy this requirement.

3. RESULTS AND DISCUSSION

Considering the trained CNN models and the YOLOv8 model, the below accuracies were recorded with the respective image enhancing algorithm as depicted in Table 1.

Table 1: Table of CNN model accuracies

Model	Image Quality			
	Original run	ESPCN	FSRCNN	ESRGAN
MobileNet	90.08	96.78	96.52	96.01
MobileNetV2	91.72	97.70	96.45	97.30
EfficientNetB0	91.23	97.18	97.25	97.15
EfficientNetB1	91.30	97.32	96.63	96.15
EfficientNetB2	91.25	97.48	96.71	96.27
EfficientNetB3	91.32	97.49	96.83	96.34
EfficientNetB4	91.45	97.46	96.92	96.42
EfficientNetB5	91.45	97.58	97.05	96.55
EfficientNetB6	91.74	97.80	97.56	97.20
NasNet	91.73	97.60	96.48	96.78
YOLOv8	98.00	99.60	99.50	98.30

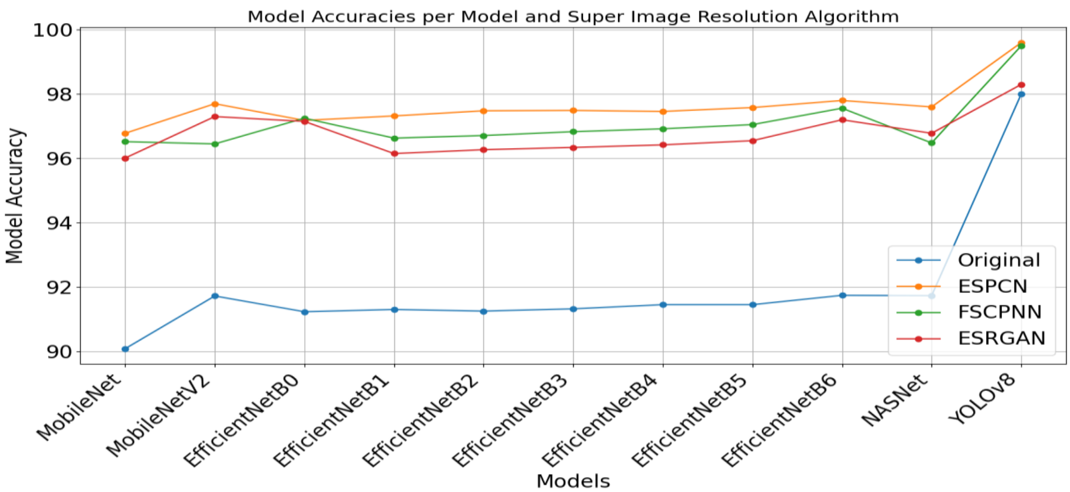

Figure 4: Line plot depicting model accuracies of the trained CNN models and YOLOv8 model

According to Table 1, the accuracy scores for models trained with enhancement techniques are consistently high, ranging from the low 90s to close to 100%. This suggests that the models are performing well on the given task of classification. Out of the CNN models, the EfficientNetB6 model when trained with ESPCN gave the highest model accuracy of 97.80.

However, all the accuracies when the image data were trained with super resolution algorithms have scored higher accuracies than when the data were comprised of original images. In all the stages of YOLOv8 model, when original images were used and when images were applied with ESPCN, FSRCNN, and ESRGAN, the model accuracies have surpassed a score of 98%. Even more, ESPCN based YOLOv8 model has scored an outstanding model accuracy of 99.60%. For better representation the model accuracies have been plotted using a line chart as shown in figure 4.

Due to the facility of having stored results of all model training executions in YOLOv8, metrics such as accuracy learning curves, loss learning curves, and confusion matrix can be obtained altogether at once (Redmon *et al.*, 2016). Figure 5 and figure 6 has depicted the loss learning curves while figure 7 has illustrated the confusion matrix of the resulting ESPCN model that was trained with the YOLOv8 model. When considering the loss curves, it is evident that the model has not been subjected to overfitting as the curves have not resulted in gaps.

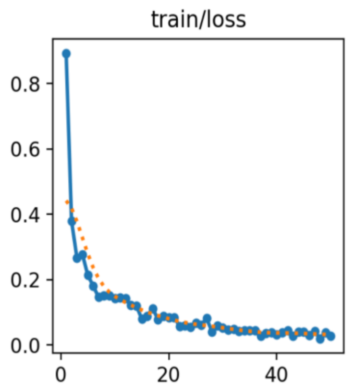

Figure 5: Training loss curve recorded by the YOLOv8 model when trained with ESPCN applied image data.

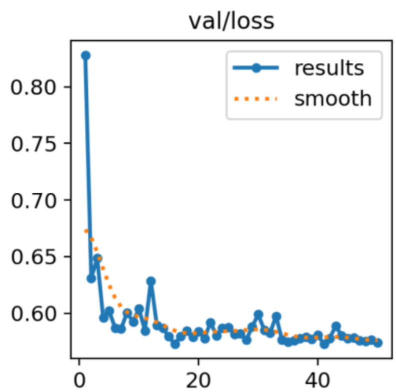

Figure 6: Validation loss curve recorded by the YOLOv8 model when trained with ESPCN applied image data.

Compared to the studies done by authors, Singh, Chug, and Singh (2022) and Elfatimi, Eryigit, and L. Elfatimi (2022) using the same type of bean leaf data, our research study has been able to obtain an improved model accuracy of 99.6% with the YOLOv8 model's outstanding performance.

According to the confusion matrix given by Figure 7, it can be further understood that the ESPCN model based on YOLOv8 has been able to classify all of the class data, having only an outlier of one prediction during the final prediction. Compared to the computational power used during the models were trained with pre-trained CNN models, the YOLOv8 model did not consume that much of resources during the model training phase. Apart from that, the YOLOv8 model was also able to handle an image size of 512 x 512, while the pre-trained models did not perform efficiently with high image sizes, which also took much time while training.

		Predicted class		
		Angular leaf spot	Bean rust	Healthy
True class	Angular leaf spot	76		
	Bean rust	1	78	
	Healthy			77

Figure 7: Resulting confusion matrix of the YOLOv-8 model when trained with ESPCN applied image data.

Figure 8: A bean rust detected leaf classified using ESPCN + YOLOv8 model.

Hence, it can be concluded that YOLOv8 is a classification model that performs optimally in bean leaf lesion classification considering its parameter efficiency and computing efficiency compared to that of EfficientNetB6. Figure 8 also depicts a sample prediction based on the ESPCN and YOLOv8 model.

4. CONCLUSION

This study was conducted using a dataset that had 1167 images of bean leaf lesion data that had three different data classes, two bean leaf disease classes and a healthy leaf class. Image enhancing methods of Fast super-resolution Convolutional Neural Networks (FSRCNN), Efficient SubPixel Convolutional Neural Networks (ESPCN), and Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) were also used to study the impact the image quality during model training phase. Rather than considering using traditional pre-trained Convolutional Neural Network models, the newly introduced YOLOv8 model was also used during the stage of model training. From the used CNN models, MobileNet, MobileNetV2, EfficientB0-B6 models, and YOLOv8, the YOLOv8 model gave an exceptional model accuracy score of 99.6% with an optimal loss learning curve and confusion matrix when the images were transformed with super resolution algorithm, Efficient Sub-Pixel Convolutional Neural Network (ESPCN). YOLOv8 also completed the model training within a very short period of time compared to the time taken by CNN models, once again proving its efficiency.

Hence, the classification of bean leaf diseases has found a crucial and resource efficient solution in the YOLOv8 model. Further studies can be conducted using further exploration into the integration of Class Activation Maps (CAM) into the bean disease classification models. This method involves identifying significant locations within bean leaf photos, providing a thorough comprehension of the regions crucial to the models' decision-making processes. Exploration of the integration of respective data models with precision agriculture technologies, such as drones or satellite imagery also can be studied considering future work as more improvements. This will enable real-time monitoring of crops at a larger scale and contribute to more proactive disease management strategies.

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