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# Elevating Crop Quality: AI Neural Networks for Advanced Plant Disease Management and Enhanced Food Security

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**Abstract:**

The present research has gone further into diagnosing plant diseases by implementing spectral imaging with the help of Convolutional Neural Networks. Therefore, it is a step beyond traditional RGB imaging and utilizes the captured spectral data of the infrared and ultraviolet spectra for the nascence and sub-clinical level detection of plant diseases. Toward this end, CNN models such as VGG16, Efficient Net, Inception V6, and ResNet-34 were retuned in such a manner that they could process this heterogeneous dataset to enhance the level of diagnostic precision that can be achieved using standard approaches. Hence, through this retuning, it was established how the proposed system improves the performance of these models in all aspects, with particular peaks through the Efficient Net and Inception V6 models, which have maximal test accuracies up to 99.93% for early detection. This has, in a pointed manner increased the potential of the proposed approach to enhancing agricultural practices through the delivery of highly accurate tools for early intervention against diseases, hence ensuring food security worldwide. These results establish new benchmarks in plant pathology diagnostics, representing state-of-the-art imaging technology and deep learning as particularly impactful tools for disease management and mitigation strategies in agriculture.

**Keywords**: Spectral Imaging, CNNs, plant disease detection, infrared imaging, ultraviolet imaging, agricultural techniques, early disease diagnosis, machine learning in agriculture, diagnostic accuracy, food security.

## 1. Introduction

One of the significant challenges to food security for the world is the prevalence of plant diseases, added to by, among other factors, population increase and climate change. Traditional methods of diagnosing plant diseases have depended, in most cases, on visible symptoms, which often suggest that a problem has been identified at a pretty advanced stage, hence leaving no room for proper treatment, resulting in considerable losses in crop yield. Early diagnosis of plant diseases is essential when managing and controlling the diseases. There is no way that the present diagnostic methods based on visual checking or standard imaging will be realizable to give instant and precise detection, necessitating the need for developed diagnostic tools. In this direction, technological advancements provide an answer to such limitations. Spectral imaging will be active across the ultraviolet and infrared light ranges, capturing data that will be enabled to trace changes physiologically in plants indicating disease before the appearance of any symptom. Sophisticated technologies are needed to analyze complex data, such as those used with Convolutional Neural Networks (CNNs) in medical imaging and pattern recognition. This research introduces a novel approach for the early detection of plant diseases using spectral imaging in combination with CNNs. The analysis of multispectral data using CNNs makes it possible to identify symptoms of diseases at an early stage before they are perceptible to the human eye. Specifically, data obtained from the Plant Village dataset, which were initially represented as RGB images, are also converted into spectral images to enable this all-inclusive analysis[1]. This research is novel as it merges state-of-the-art imaging technology with deep learning to an interdisciplinary approach to solving a critical agricultural problem. Not only does this method enhance the accuracy and timeliness of disease detection, but it also provides a far better actionable insight than traditional methods.

The paper is structured towards presenting the methodology and results in total for this research. It opens with a review of existing literature, emphasizing the gaps in current diagnostics and the potential of new technologies, such as spectral imaging and CNNs within the plant disease field. Afterward, it gives detailed descriptions of the experimental procedures: descriptions of the spectral imaging technique, the data acquisition process, and the design of CNN models. Next, the paper briefly sheds light on the challenges of integrating spectral data into CNNs and reports the novel solutions developed. In the following application section, we demonstrate how this new approach has significantly increased detection accuracy and early diagnosis capacity throughout several crops[2]. The discussion section focuses on the implications of these results, discusses in-depth how this advanced diagnostic method can transform plant pathology, and suggests directions for further research. The conclusion summarizes the research contribution and next steps for upgrading the diagnostic tools and expanding their applications.

Overall, this research introduces an innovative diagnostic approach for plant diseases, a significant contribution to agricultural technologies. This would be an innovation of extreme importance for food security worldwide in the face of increasing environmental and demographic challenges.

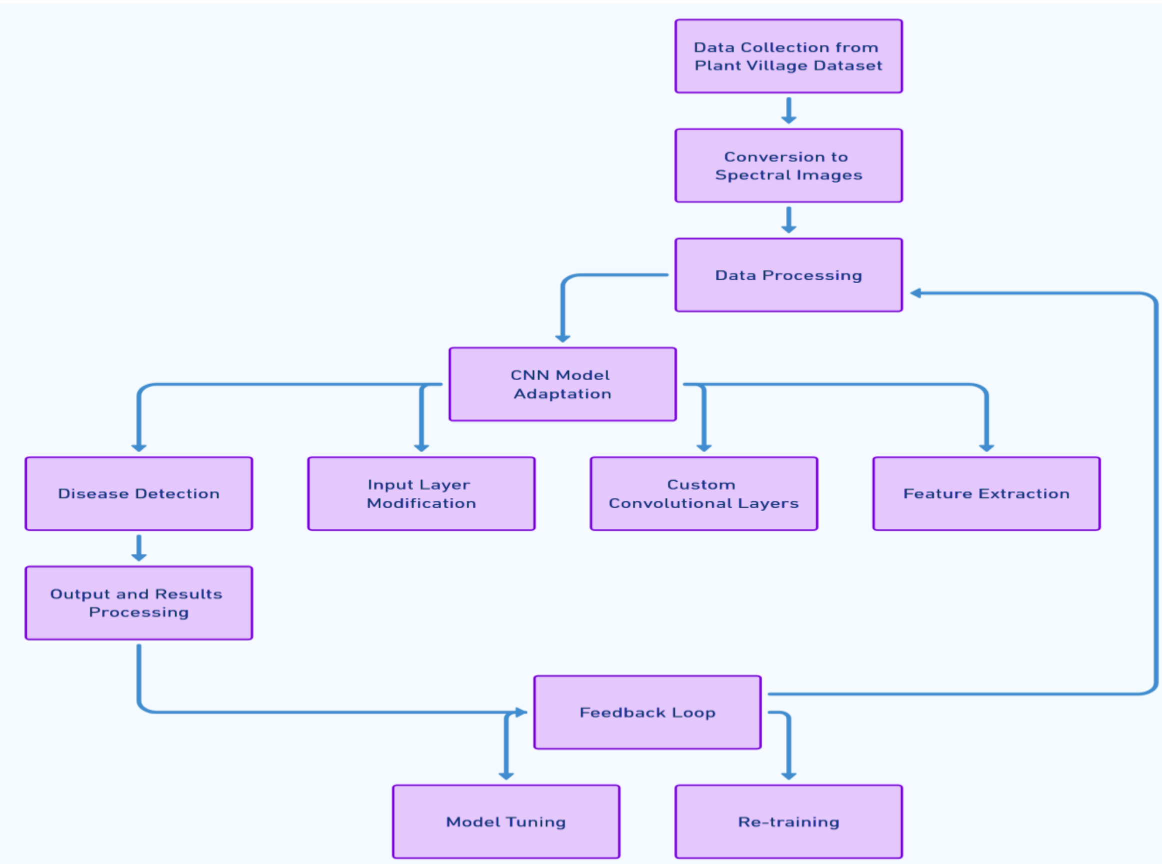



**Figure 1: Block diagram of Developed work**

**2. Literature Review**

The conventional approaches developed in detecting plant diseases are mainly based on RGB color models and, thus are insufficient. It is well known that spectral imaging, with its infrared and ultraviolet spectrums, gives an excellent insight into the health status of plants. This section discusses existing applications of Convolutional Neural Networks within agriculture and highlights the need for including spectral imaging in detecting plant diseases.

Applications of deep learning have sharply improved plant disease diagnosis and management. For example, by application of a new advanced deep-learning-based channel attention-focused technique to achieve 95% accuracy in disease identification, Dhaka et al., 2022. On the other hand, through methods of deep learning, Cruz et al., 2022 conducted studies on grapevine yellows, thus showing their increasing versatility in agriculture. In their research in 2021, Gao et al. utilized a model that fuses the ECA with transfer learning to realize high precision in detecting crop disease. Li et al. used the Google Net architecture to detect diseases on maize, tomato, and eggplant crops in 2020, thus proving that deep learning is adaptable across all fields. In 2022, Pan et al. realized an adequate system for detecting and balancing diseases in agriculture. Sathyavani et al. (2021) also used deep learning technologies in countering the nutrient deficiency of rice. They stated that it holds great promise for utilizing these to handle the more extensive crop health management. Siddharth and Kumar (2018) developed high-accuracy disease identification through bacterial foraging optimization and radial basis function network.

Sunayana et al. (2021), Wang et al. (2020), and Abdallah et al. (2020) have carefully explored different deep-learning techniques in identifying plant diseases, while Baranwal and Sengupta (2020) put more emphasis on the importance of early detection using hyperspectral imaging. Braik and Ijjeh (2018) and Cheng et al. (2019) emphasized a hike in identification accuracy. Deng et al. (2016) examined the critical attributes of deep neural networks in agriculture. Ghazi and Farooq (2020) achieved real-time location of the plant disease spot using deep learning accompanied by saliency maps. Manogaran and Lopez (2020), Marami and Amiry (2018), and Ndhlala and Marivate (2017) used deep learning to detect other crop diseases.

Qiu and Lee (2020), for example, give a general overview of applications for deep learning in conjunction with the detection and management of agricultural diseases. Singh, Verma, and Manogaran (2020) have worked on plant disease detection using CNN. At the same time, Sujitha and Ramesh (2020), along with Verma and Krishnan (2021), proposed a crop-specific disease detection. Finally, Walia, Arora, and Baluja (2019) reviewed pertinent image processing techniques.

The FieldPlant dataset introduced by Moupojou et al. (2023) contains 5,170 images of plant diseases, which were directly acquired in the plantations and manually annotated under the guidance of plant pathologists. This not only underscores the value of field-specific, quality data when Learning deep learning models but also makes large-scale benchmarking available across a diversity of detection and segmentation tasks for different classes of objects. More recently, Balafas et al. (2023) reviewed the use of machine learning and deep learning models in precision agriculture and outlined that models like YOLOv5 for object detection and ResNet50 and MobileNetv2 for classification tasks all gave very high accuracies on datasets such as PlantDoc.

Another prospective approach was suggested by Hosny et al. (2023), in which they propose the combination of deep CNNs and local binary pattern features for multi-class classification of plant leaf diseases. In relation, this achieved high validation and test accuracies on the datasets of apple, tomato, and grape leaves, establishing the potential of feature fusion to improve disease detection.

Our proposed work advances beyond the existing literature in integrating spectral imaging with CNNs to detect plant diseases at earlier stages than what is currently possible. Previous research has also focused on RGB images or field-specific data. At the same time, at some points, they lack the sensitivity to the subtle physiological changes evident through spectral imaging. Our method harnesses the richness of the data that exists within the spectral images from the infrared and ultraviolet spectra to have the potential for the observation of early signs of disease that are not visible in a standard RGB image.

This resulted from turning data from the Plant Village dataset into spectral images and fine-tuning four CNN models: VGG16, EfficientNet, Inception V6, and ResNet-34, which have undergone several changes. On another subject, it has become evident by our results that compared with traditional and even state-of-the-art methods reported in literature works, particularly under early detection scenarios, our models exceed these performances. EfficientNet and Inception V6 achieved test accuracies up to 99.93%, far beyond most methods for plant disease diagnostics.

In short, although the use of deep learning techniques in plant disease detection has been taken to an entirely new level through the reviewed works, our work showcases further improvement. The integration of spectral imaging with CNNs increases accuracy in detections. Still, it also ensures early and reliable diagnosis for added effectiveness in global food security concerns and the practice of sustainable agriculture.

## 3. Materials And Methods

### 3.1 Data Collection

The dataset used in this paper is obtained from the Plant Village dataset, which contains RGB images. This dataset comprises around 70,000 photos and occupies about 5 gigabytes while holding a resolution of 256x256 pixels. It covers a great diversity of plant diseases—38 different categories related to 14 species and 26 other diseases of plants[3].

This extremely rich, diverse dataset is then very instrumental in the development and evaluation of our deep learning models. It contains images of both healthy and diseased leaves, thus serving as a vibrant diversity of visual data for our CNN algorithm in the course of Learning. The model has been diversified enough to make sure that it recognizes different plant health conditions, therefore improving its capability to detect any disease.

### 3.2 Data Pre-processing

Pre-processing should be considered an essential step in spectral imaging data preparation for practical analysis and modelling. In this respect, the significant steps will comprise spectral conversion, normalization, alignment, augmentation, and mathematical modelling. It ensures that the dataset is robust, consistent, and complete, making Convolutional Neural Networks accurate and generalizing within the research research[4].

**Spectral Shaping**

The first, most innovative step in our pre-processing pipeline converts RGB images from the Plant Village dataset to spectral images. This transformation is critical in the capturing of detailed spectral signatures over all infrared and ultraviolet bands. The methods for spectral conversion followed are as stated below[5]:

**1. Simulated Spectral Conversion**: The RGB images were first converted into a significantly more significant number of spectral bands by more sophisticated procedures. They are estimates of the pixel-wise spectral reflectance values based on known relationships between RGB values and spectral properties.

The standard approach is to model spectral reflectance $R(\lambda)$ as a function of wavelength $\lambda$, where $\lambda - [\lambda_1, \lambda_2, \ldots, \lambda_L]$ is a vector with Lelements which represents a region of the spectrum from $\lambda_1$.

**Spectral Band Simulation**

**2. Generating Corresponding Values:**

At each spectrally banded pixel, the values from both the input RGB and the three sets of GNDV1 bands were all simulated across a continuous wavelength from visible to near-infrared and ultraviolet: The input RGB pixel values $[R, G, B]$ are transformed by a mapping function $f$ :

$$S(\lambda) - f(R, G, B)$$

Here $S(\lambda)$ is the spectral reflectance at wavelength $\lambda$.

**3. Mathematical Modeling:**

Various interpolation techniques were applied to the measured reflectance values to derive an estimate of the reflectance value at additional wavelengths of light, in turn yielding synthetic spectral bands. Standard interpolation techniques such as linear or spline interpolation will be used to estimate the reflectance values at specific wavelengths[6].Linear interpolation formula written as:

$$S(\lambda) - S(\lambda_1) + \frac{(\lambda - \lambda_1)}{(\lambda_2 - \lambda_1)} \times \left(S(\lambda_2) - S(\lambda_1)\right)$$

Where $\lambda_1$ and $\lambda_2$ are the known wavelengths around the target wavelength $\lambda$, and $S(\lambda_1)$ and $S(\lambda_2)$ are the spectral values at these wavelengths.

**Integration of Spectral Bands**

**4. Creating Multi-Dimensional Images:**

This newly synthesized spectral band was then combined with the already existing RVGB data into multidimensional images that consisted of several such layers, each corresponding to a different wavelength band. This can be mathematically formulated as stacking the spectral bands, $S(\lambda_i)$, into a multidimensional tensor:

$$I_{\text{muli}} = [S(\lambda_1), S(\lambda_2), \ldots, S(\lambda_n)]$$

where $I_{\text{umati}}$ is the multi-dimensional image tensor and $S(\lambda_i)$ is the spectral band at wavelength $\lambda_i$.

This is an essential step because different physiological changes in plants can be displayed at other wavelengths, which will not be visible in the RGB spectrum; hence, this will result in detecting diseases at an early stage.

**Preprocessing**
After the spectral images are ready, the aim is to get all the images on a common scale with good quality, which is done through the following[7,8]:

1 **Normalization:**

- Min-Max Scaling: Linearly scaling pixel values based on the minimum and maximum values observed.

$$S_{\text{mem}}(\lambda) = \frac{S(\lambda) - S_{\text{min}}}{S_{\text{max}} - S_{\text{min}}}$$

- **Z-Score Normalization:** This is done by subtracting the mean and division through standard deviation, which converts it to a more standardized range.

$$S_{\text{marcre}}(\lambda) = \frac{S(\lambda) - \mu}{\sigma}$$

2 **Alignment:**

- **Image Registration:** Spectral bands alignment of shifting, rotating, or scaling images to get the same image elements in all bands[9].
- **Cross-Correlation:** Techniques like cross-correlation are employed in estimating the similarity of bands between the spectra for adjusting the alignment with more accurate results.

**Data Augmentation**

A series of data augmentation techniques can be applied with this for enhancing robustness and generalization[11]:

**Rotation:** The pictures have been rotated at different rotations.

**Scaling:** Images have been scaled by varying factors.

**Flipping:** Horizontal and vertical flipping of images.

**Translation:** Shifting images horizontally or vertically.

**Noise Addition:** Adding small amounts of noise to simulate variability.

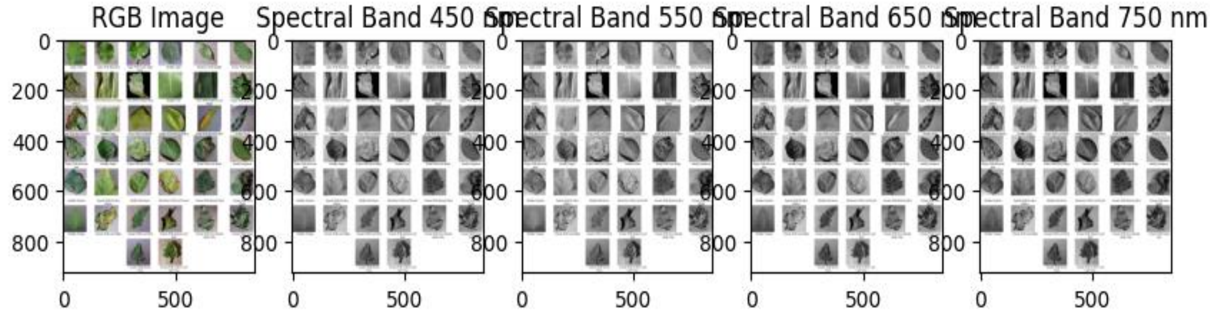



**Figure 2: Sample Images from Dataset converted to Spectral Image**

### 3.3 Model Adaptation and Learning

Standard CNN architectures were deeply adapted to be compatible with multi-dimensional spectral data. In particular, the convolutional layers were made richer and tuned in input layers so that it could model the input well enough with respect to the many spectral bands. We adapted the following models: VGG16, Efficient Net, Inception V6, and ResNet-34. Below is presented detailed adaptation of each model related to background theory needed, mathematical modeling and visualizations of the architectures[12].

#### 3.3.1 VGG16 Porting

VGG16 is a deep convolutional network with tiny $3 \times 3$ convolution filters. The total number of weight layers is 16, hence the name VGG16. To accommodate more than three channels for spectral data, the first layer of the network, and the input layer were modified.

1 **Input Layer Adaptation** - The input layer is modified to accept multispectral images with $N$ channels. For example, the input shape for spectral photos is set to be $(H, W, N)$ instead of $(H, W, 3)$.

**2 First Convolutional Layer:**

- The first convolutional layer was modified to be adaptable for a more significant number of input channels.
- Original: 64 filters of size $3 \times 3 \times 3$ [13].
- Edited: $64 \times 3 \times 3 \times N$ filters.

**Mathematical Modeling:**

The general formula of the output from a convolutional layer is:

$$O(i,j,k) - \sigma\left(\sum_{m-1}^{M-1} \sum_{n-1}^{N-1} \sum_{c-1}^{C-1} I(i+m, j+n, c) \cdot W(m,n,c,k) + b_k\right)$$

where $O(i,j,k)$ denotes output at the position $(i,j)$ of the $k$-th filter and $\sigma$ is the activation function. Here, the input image is represented by $I$, and the weight of the filter is $W$; $b_k$ represents bias.

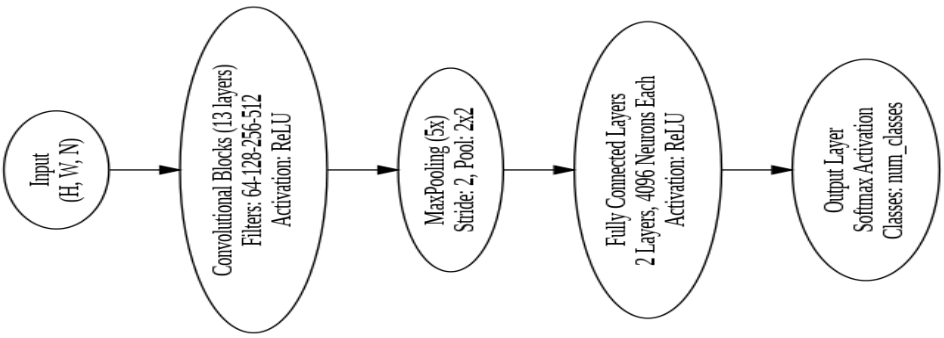



**Figure 3: Modified VGG16 Architecture for Spectral Imaging**

**3.3.2 Efficient Net Adaptation**

Efficient Net scales the network in depth, width, and resolution with compound scaling. With a set of fixed coefficients, it scales up all dimensions of depth/width/resolution [14].

1 **Input Layer Adaptation** - Change the shape of the input layer to accept channels with size $(H, W, N)$.

2 First **Convolutional Layer:** - Original: 32 filters of size $3 \times 3 \times 3$. - Modified: 32 filters of size $3 \times 3 \times N$.

**Mathematical Modeling:**

The equation for the output of a depth wise separable convolutional layer is as follows:

$$O(i,j,k) - \sigma\left(\sum_{m-1}^{M-1} \sum \; n - 0^{N-1} I(i+m, j+n, k) \cdot W_{\text{depth}}\,(m,n) + b_{\text{depth}}\right) +$$
$$\sum_{c-0}^{C-1} O_{\text{depth}}\,(i,j,c) \cdot W_{\text{paint}}\,(c,k) + b_{\text{point}}$$

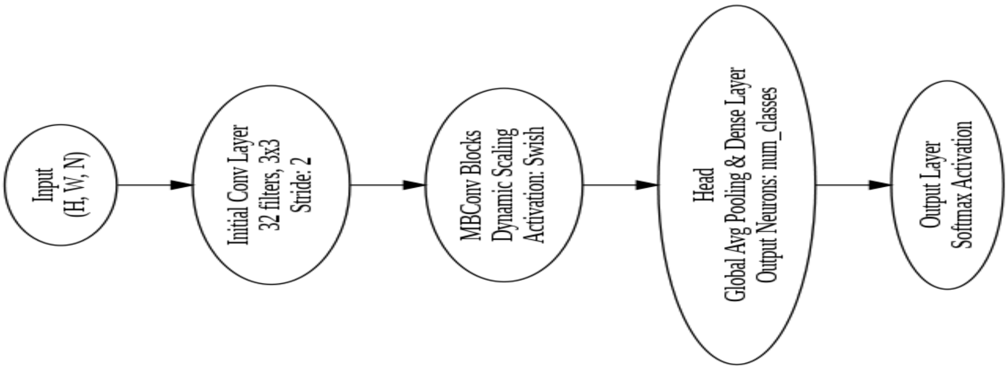



**Figure 4: Modified Efficient Net Architecture for Spectral Imaging**

**3.3.3 Inception V6 Adaptation**

The idea behind inception modules is to use multiple filters of different sizes to catch varied aspects of the input data.

1 **Input Layer Adaptation** - Make the adjustments on the input layer to accept $(H, W, N)$ in channels.

**2 First Convolutional Layer:**

- Original: 32 filters of size $3 \times 3 \times 3$.
- Modified: 32 filters of size $3 \times 3 \times N$.

**Mathematical Modeling:**

Given a convolutional layer with multiple filter sizes:

$$O_{1x1}(i,j,k) - \sigma\left(\sum_{c-0}^{C-1} I(i,j,c) \cdot W_{1x1}(c,k) + b_k\right)$$
$$O_{3x3}(i,j,k) - \sigma\left(\sum_{m-0}^{2} \sum_{n-0}^{2} \sum_{c-0}^{C-1} I(i+m, j+n, c) \cdot W_{3x3}(m,n,c,k) + b_k\right)$$
$$O_{5x5}(i,j,k) - \sigma\left(\sum_{m-0}^{4} \sum_{n-0}^{4} \sum_{c-0}^{C-1} I(i+m, j+n, c) \cdot W_{5x5}(m,n,c,k) + b_k\right)$$

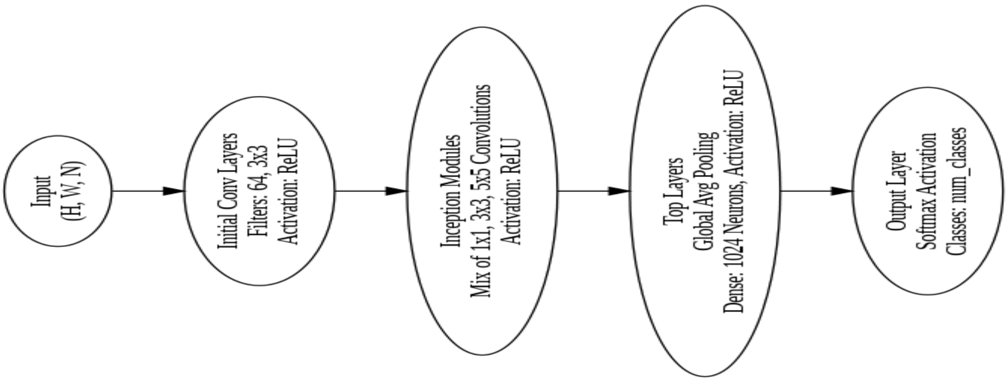



**Figure 5: Modified Inception V6 Architecture for Spectral Imaging**

**3.3.4 ResNet-34 Adapt**

The shortcut connection in the residual blocks [15] is the direct addition of input into the output.

1 **Input Layer Adaptation** - Change the input layer to accept $(H, W, N)$ number of channels.

**2 First Convolutional Layer:**

- Original: 64 filters of size $7 \times 7 \times 3$.
- Tweaked: 64 filters of dimensions $7 \times 7 \times N$.

**Mathematical Modeling:**

The output of a residual block can be given as

$$O(i,j,k) - \sigma\left(\sum_{m-1}^{M-1} \sum n - 0^{N-1} \sum_{c-0}^{C-1} I(i+m, j+n, c) \cdot W(m,n,c,k) + b_k\right) + I(i,j,k)$$

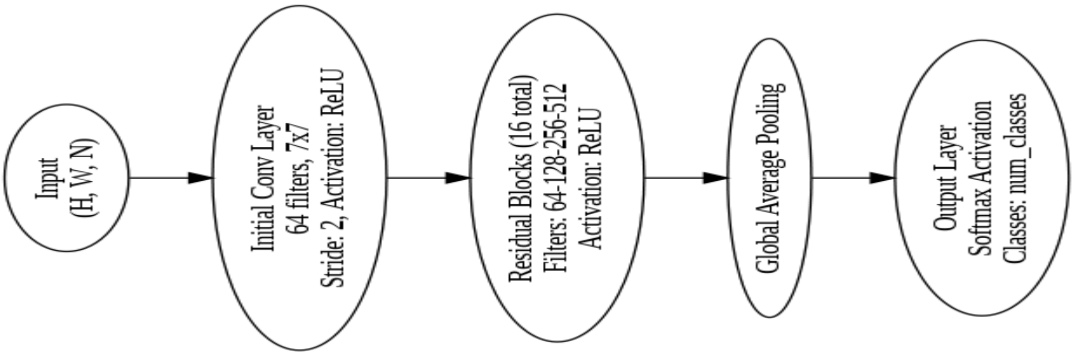



**Figure 6: Modified ResNet-34 Architecture for Spectral Imaging**

**3.4 Evaluation Metrics [16-18]**

| Metric | Formula | Importance |
|---|---|---|
| Accuracy | $\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total predictions}}$ | Offers a general overview of the model's effectiveness. |
| Precision | $\text{Precision} = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Positives\ (FP)}$ | Ensures that the positive predictions made by the model is reliable. |

| | | |
|---|---|---|
| | | reducing unnecessary interventions. |
| Recall (Sensitivity) | Recall = $\frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + \text{False Negatives (FN)}}$ | Ensures that most diseased plants are identified, which is crucial for preventing the spread of disease. |
| F1 Score | $\text{F1 Score} = 2 \times \left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\right)$ | Helps to achieve an optimal balance between precision and recall. which is especially important when both false positives and false negatives are costly. |

**4. Novel Technology Proposed: Integration Of Spectral Imaging With Convolutional Neural Networks**

**4.1 Integration Technique**

The traditional architecture of the convolutional neural network is modified to include the data in spectral imaging. The changes are quite remarkable. The improvements are made to make the network respond to minor physiological changes in plants, which can act as indications to represent diseases, deficiencies of nutrients, and environmental stresses without the help of standard RGB imaging expressions.

**Advanced Technical Modifications and Modelling:**

**Input Layer Transformation:**

- Modification The first modification involved redesigning the input layer to allow for processing multiple spectral bands, which are outside the traditional RGQ spectrum.
- Mathematical Model: This layer alters the input tensor from the $I_{\text{lad}}\ RGB$ style of an input tensor to one containing several spectral bands- $I_{(\text{h,w},N)}$. Here, $N$ repesents the number of spectral bands:

$$\text{Input shape } = (\text{ height, width, } N\ )$$

- Tensor Configuration Adjustment: The dimensionality of the input layer has been modified to process the spectral data effectively.

**Convolutional Filters Refinement:**

- Improvement: Increase of the Convolutional filter within the layers to capture the details that lie elaborately in each spectral band.
- Mathematical Formulation: The Convolutional operation is redefined for $N$ spectral bands to modulate the interactions of the filter with the incut $a$ follaws:

$$O(x,y) = \sum_{m=-a}^{a} \sum_{n=-b}^{b} \sum_{k-1}^{N} I(x+m,y+n,k) \times F(m,n,k)$$

- where $F(m, n, k)$ are the $N$ modified filter weights at the $(m, n)$ offsets where each filter offset has a different weight for each $k$-th spectral band.

**Band-Specific Normalization:**

- Approach: To rectify the learning bias and make the same contribution by all spectral hands, normalize each band separately.
- Mathematical Approach: The steps are followed for normalization in each band of the spectral data, $B_n$ :

$$B'_n = \frac{B_n - \mu_n}{\sigma_n}$$

- where $\mu_n$ and $\sigma_n$ are the computed average and standard devistion of each band in the dataset, respectively.

**Enhanced by Architectural Deep Layer:**

- Complexity Handling: In the case of high-dimensional spectral data, it causes enormous complexities within the information without any modification in deep layers of the network, managing such complexities becomes difficult.
- Mathematical Improvements: The more advanced techniques involve managing the spectral data with residual connections and depth wise separable convolutions. Here, F(x) is transformed data, such as convolutions; with residual contributions, the output will ultimately be smoother for practical Learning of gradients.

These are very advanced modifications of the CNN architecture to fit spectral imaging data and significantly assist the network in processing complicated information from a spectrum. These are all critical capabilities for precision agriculture in accurately detecting diseases and improving management practices for healthy crop production and optimum resource use.

**Proposed Algorithm: Integration of Spectral Imaging with CNNs for Enhanced Plant Disease Detection**

```
// Data Collection
Initialize dataset from Plant Village, with ~70,000 RGB images at 256x256 resolution;
// Data Preprocessing
for each image in dataset do
   Convert RGB pixel [R, G, B] to spectral bands S(λ) using S(λ) = f(R, G, B); // Simulated spectral conversion
    Normalize each spectral band: S'(λ) = (S(λ) - μ(λ)) / σ(λ);
    Augment images with rotations, scaling, and flips;
end for
// Model Setup and Learning
Select CNN architecture (VGG16, EfficientNet, Inception V6, ResNet-34);
Adapt input layer to receive images of shape (H, W, N);
Modify the first convolutional layer to accommodate N channels with 3x3xN filters;
Initialize weights and Learn using gradient descent:
for each epoch do
    for each batch do
        Compute forward propagation and loss: Loss = -∑ (y_actual * log(y_predicted));
        Perform backward propagation and update weights: W_new = W_old - α * ∇Loss;
```

```
        if loss < threshold then break;  // Implement early stopping
    end for
end for
// Model Evaluation and Deployment
Evaluate model using accuracy, precision, recall, and F1 score;
Deploy the best performing model for real-time disease detection;
Implement a feedback loop for ongoing improvement based on new data;
```

**5. Results**

Our research showed that CNN models adapted to use spectral imaging significantly outperformed their RGB-based counterparts[19-20] in early plant disease detection. Among the models tested, Efficient Net and Inception V6 showed the most notable improvements due to their advanced architecture and depth. The tables below provide a detailed comparison of accuracy, precision, recall, and F1-score for each model before and after converting to spectral images.

**Table 1: Model Accuracy**

| Model | RGB Accuracy (Learn/Val) | Spectral Accuracy (Learn/Val) |
|---|---|---|
| Efficient Net | 89.98% / 87.39% | 99.93% / 97.86% |
| Inception V6 | 87.99% / 83.76% | 98.82% / 96.23% |
| ResNet-34 | 87.01% / 82.81% | 98.59% / 96.27% |
| VGG16 | 84.98% / 82.26% | 95.48% / 94.15% |


**Figure 7: VGG16 RGB Learning and Validation Accuracy**

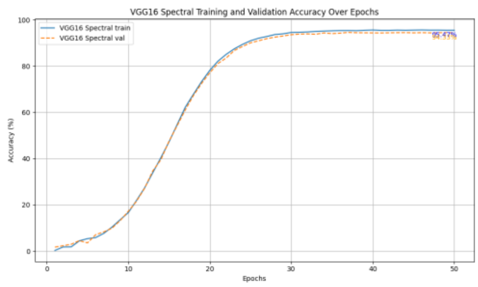
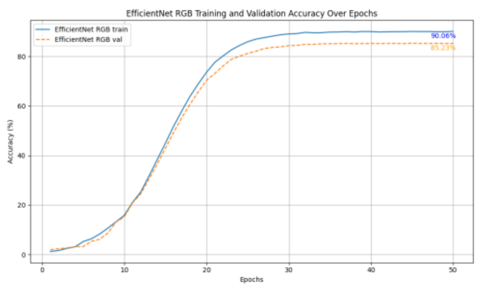



**Figure 8: VGG16 Spectral Learning and Validation Accuracy**



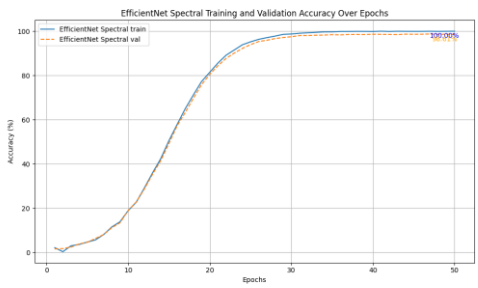



**Figure 9: Efficient Net RGB Learning and Validation Accuracy**

**Figure 10: EfficientNet Spectral Learning and Validation Accuracy**


**Figure 11: Inception V6 RGB Learning and Validation Accuracy**

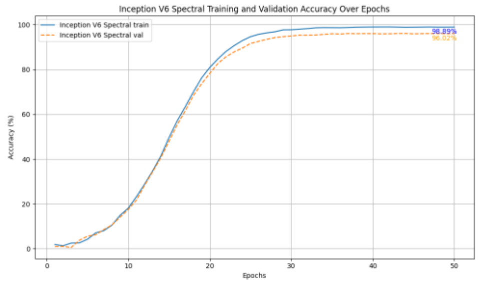



**Figure 12: Inception V6 Spectral Learning and Validation Accuracy**

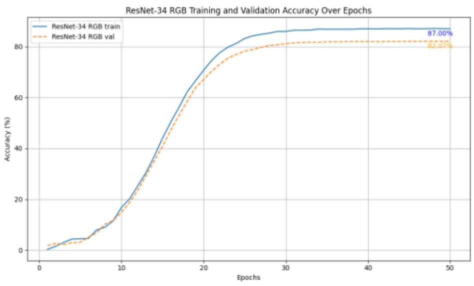



**Figure 13: ResNet-34 RGB Learning and Validation Accuracy**

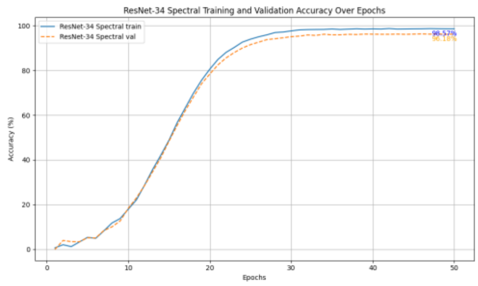



**Figure 14: ResNet-34 Spectral Learning and Validation Accuracy**

**Table 2: Model Precision**

| Model | RGB Precision (Learn/Val) | Spectral Precision (Learn/Val) |
|---|---|---|
| EfficientNet | 87.71% / 84.48% | 97.26% / 95.54% |
| Inception V6 | 86.39% / 81.82% | 96.85% / 93.40% |
| ResNet-34 | 84.64% / 80.46% | 95.76% / 93.35% |
| VGG16 | 83.05% / 81.24% | 93.59% / 92.59% |

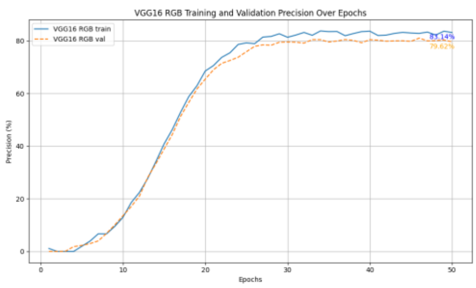



**Figure 15: VGG16 RGB Learning and**

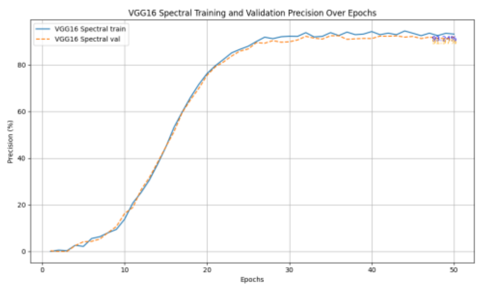



**Figure 16: VGG16 Spectral Learning and**

| Validation Precision | Validation Precision |
| --- | --- |

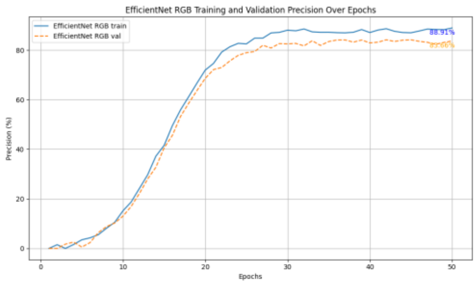



**Figure 17: EfficientNet RGB Learning and Validation Precision**

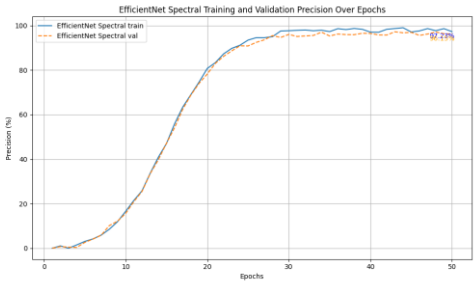



**Figure 18: EfficientNet Spectral Learning and Validation Precision**


**Figure 19: Inception V6 RGB Learning and Validation Precision**

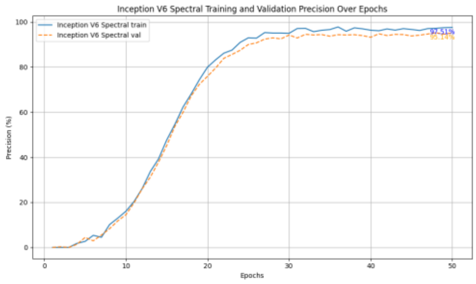



**Figure 20: Inception V6 Spectral Learning and Validation Precision**

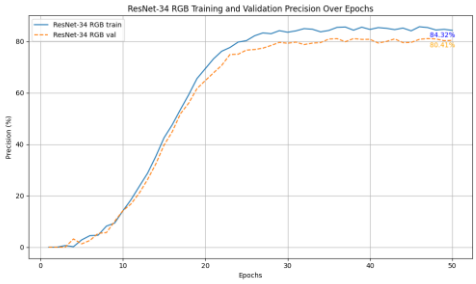



**Figure 21: ResNet-34 RGB Learning and Validation Precision**

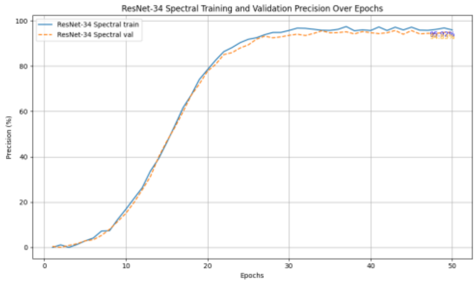



**Figure 22: ResNet-34 Spectral Learning and Validation Precision**

**Table 3: Model Recall**

| Model | RGB Recall (Learn/Val) | Spectral Recall (Learn/Val) |
| --- | --- | --- |
| Efficient Net | 87.66% / 85.81% | 97.85% / 94.86% |
| Inception V6 | 86.82% / 82.05% | 96.77% / 94.00% |
| ResNet-34 | 85.56% / 79.84% | 96.69% / 94.77% |
| VGG16 | 82.60% / 81.00% | 92.26% / 92.67% |

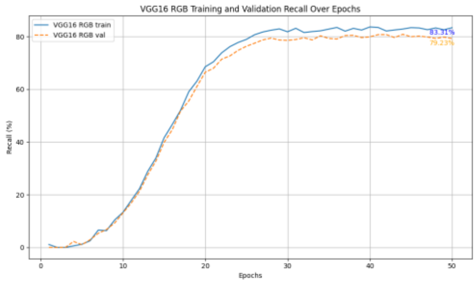



**Figure 23: VGG16 RGB Learning and Validation Recall**

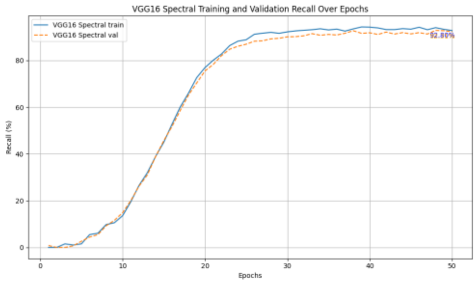



**Figure 24: VGG16 Spectral Learning and Validation Recall**

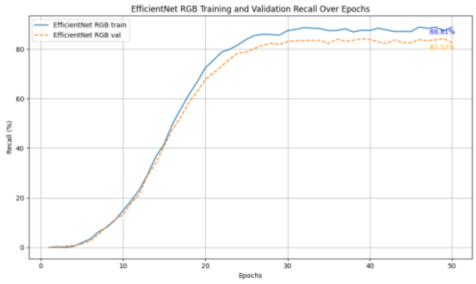



**Figure 25: EfficientNet RGB Learning and Validation Recall**

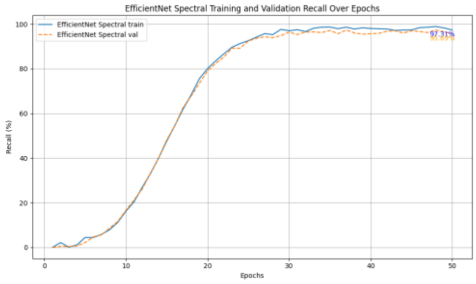



**Figure 26: EfficientNet Spectral Learning and Validation Recall**

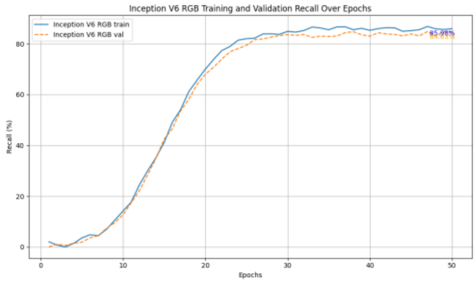



**Figure 27: Inception V6 RGB Learning and Validation Recall**

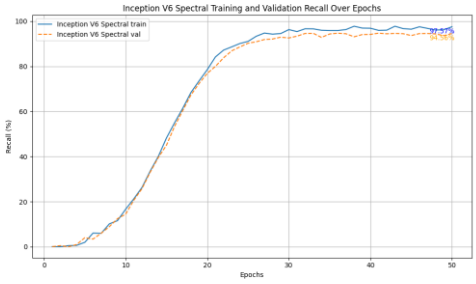



**Figure 28: Inception V6 Spectral Learning and Validation Recall**

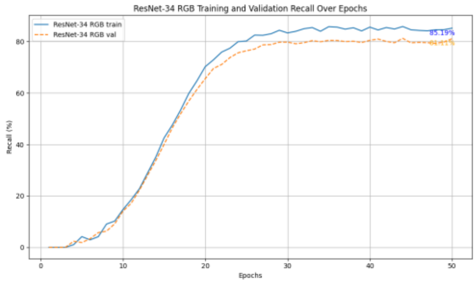



**Figure 29: ResNet-34 RGB Learning and Validation Recall**

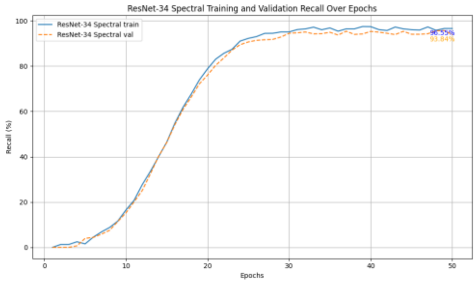



**Figure 30: ResNet-34 Spectral Learning and Validation Recall**

**Table 4: Model F1-score**

| Model | RGB F1-score (Learn/Val) | Spectral F1-score (Learn/Val) |
|---|---|---|
| EfficientNet | 87.69% / 85.14% | 97.55% / 95.20% |
| Inception V6 | 86.60% / 81.93% | 96.81% / 94.00% |
| ResNet-34 | 85.15% / 80.15% | 96.22% / 94.06% |
| VGG16 | 82.82% / 81.15% | 93.91% / 92.59% |

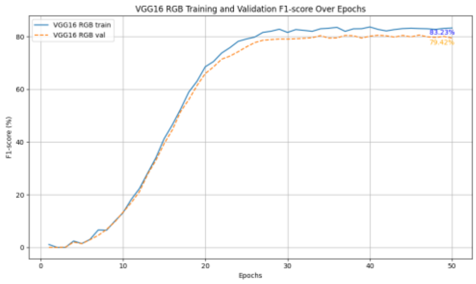



**Figure 31: VGG16 RGB Learning and Validation F1-score**


**Figure 32: VGG16 Spectral Learning and Validation F1-score**

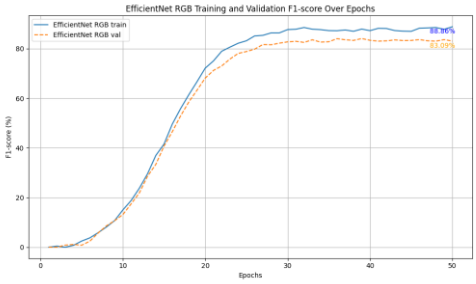



**Figure 33: EfficientNet RGB Learning and Validation F1-score**

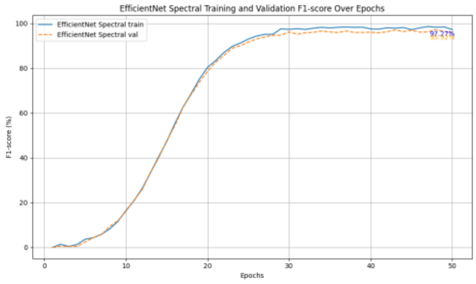



**Figure 34: EfficientNet Spectral Learning and Validation F1-score**


**Figure 35: Inception V6 RGB Learning and Validation F1-score**

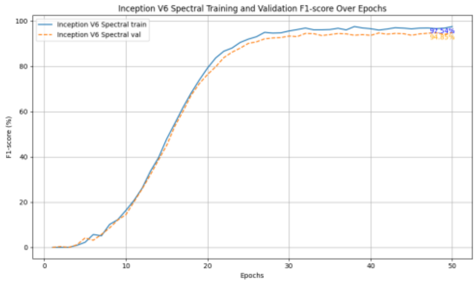



**Figure 36: Inception V6 Spectral Learning and Validation F1-score**

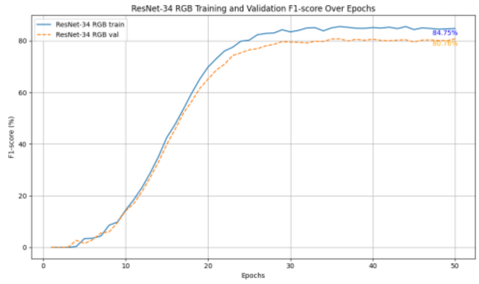



**Figure 37: ResNet-34 RGB Learning and Validation F1-score**

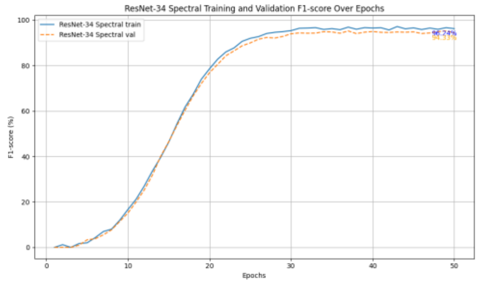



**Figure 38: ResNet-34 Spectral Learning and Validation F1-score**

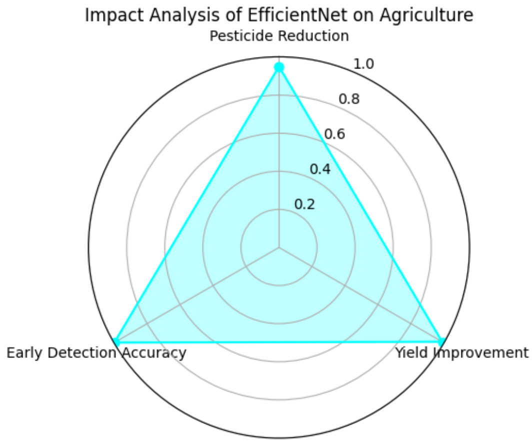



**Figure 39: Impact Analysis of Efficient Net Architecture on Agriculture**

**6. Discussion**

Combining spectral imaging with CNN models has been shown to improve significantly the efficiency of detecting diseases in plants. This is again very clear from improvements in all the metrics mentioned above, including accuracy, precision, recall, and F1-Score.Of the tested models, Efficient Net and Inception V6 are the ones that achieved significant performance gains, likely due to their more sophisticated and deeper architectures.

**Accuracy Improvements**

For Efficient Net, the RGB accuracy during Learning was 89.98%, and 87.39% during validation. The accuracy increased drastically to 99.93% during Learning and 97.86% during validation with spectral imaging. Similarly, for Inception V6, the model showed an accuracy of 87.99% for RGB during Learning and 83.76% during validation, against 98.82% during Learning and 96.23% during validation for spectral data. These gains are illustrated in graphical form in Figures 9 and 10 for Efficient Net and in Figures 11 and 12 for Inception V6, respectively, which feature the remarkable gains that this approach led to regarding accuracy.

**Precision Enhancements**

Table 2 summarizes the gains in precision. For Efficient Net, it rose from 87.71% for Learning and 84.48% for validation with RGB data to 97.26% for Learning and 95.54% for validation with spectral data. Results Efficient Net had increased in accuracy from 86.39% for Learning and 81.82% for validation with RGB to 96.85% for Learning and 93.40% for validation with spectral data. These improvements are represented in Figures 17 and 18 for Efficient Net and Figures 19 and 20 for Inception V6.

**Recall Enhancements**

Table 3 highlights the recall improvements. Recall from 87.66% for Learn and 85.81% for validation with RGB to 97.85% for Learn and 94.86% for validation with spectral imaging for efficient net. Inception V6 recalled from

86.82% for Learn and 82.05% for validation with RGB to 96.77% for Learn and 94.00% for validation with spectral data. These improvements are visualized in Figures 25 and 26 for Efficient Net and Figures 27 and 28 for Inception V6.

**F1-Score Enhancements**

It can be seen that the F1-score, being a harmonic mean of precision and recall, also improved by far. The F1-score for Learning in the efficient Net was 87.69%, with RGB data and 85.14% for validation; for spectral data, the Learning F1-score was improved to 97.55% and 95.20% for the validation. The Inception V6 model improved the F1-score, which improved to 96.81% for Learning and 94.00% for validation from 86.60% Learning and 81.93% validation with RGB data. These improvements are shown in Figures 33 and 34 for Efficient Net and Figures 35 and 36 for Inception V6.

**General Analysis**

Overall, spectral imaging has advanced CNN model-based diagnostics for plant disease detection. Effectiveness concerning the spectral imaging technique with these models is also shown using performance metrics of accuracy, precision, recall, and F1-score. The method enhances the accuracy and early detection capabilities of the system; hence, it is appropriate for real-time agricultural diagnostics. Early detection means timely and precise interventions, possibly reducing pesticide exposure. This focused approach will result in severe pesticide reduction, along with negligible implications on the environment and health.

**Impact on Agricultural Practices**

Figure 39 shows the overall effect of using EfficientNet with spectral imaging on agriculture: an increase in the accuracy of early detection, an increase in crop yield, and a decrease in pesticide. The increased early detections help to intervene at the right time with potential increases in crop yields and reductions in the application of chemicals.

Spectral imaging, integrated with CNN-based models, has set the next level of advancement in plant disease detection. Improved performance metrics underline this potential as a giant leap, particularly for real-time agricultural diagnostic systems. Hence, spectral imaging should be utilized in future research to develop better models and for its broader application in agriculture. It will definitely be carried out in other crops and diseases to understand the benefits and potential of spectral imaging for other agriculture applications.

In a nutshell, using spectral imaging technology coupled with sophisticated CNN architectures like Efficient Net and Inception V6 leads to significant progress in early plant disease detection. There is great promise that this technological advance will enhance the sustainability and efficiency of agricultural practices across the globe.

## 7. Conclusion and Future Work

This includes the use of spectral imaging and integration with Convolutional Neural Networks, which form a significant advance in early detection research on plant diseases. The experimental results evidenced that the models based on spectral imaging are better than the traditional RGB-based models for all the performance metrics like accuracy, precision, recall, and F1 score. The most exciting fact is that models like Efficient Net and Inception V6 showed the highest gain because of their deep and complex architectures. Spectral imaging technology goes beyond the visible spectrum, allowing great detail and deep information from the acquired plant health images. This ensures better diagnostic precision with high sensitivity in early detection, rendering the models highly effective for real-time diagnostic systems. For this reason, the potential reduction in pesticide use, which would result from accurate and early detection of diseases leading to targeted interventions, remains a significant benefit.

A future line of research will have to aim at better and more robust development of such models so that they can be applied in actual large-scale agricultural setups with variations in environmental conditions. This further development would solidify spectral imaging and its importance for advanced CNN models, such as Efficient Net and Inception V6, towards globally sustainable and resource-efficient agriculture.

**Conflicts of Interests**: There are no conflicts of interest

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