Plant Disease detection using CNN

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***I. Abstract:***

***Plant diseases must be detected early and correctly in reducing crop loss and food security. Such methods of identification, rooted in expert opinion, are tedious, expensive, and prone to accidents, especially for large-scale farming. The study proposes a deep-learning approach that automates plant disease detection using image-based analysis. The Proposed system, by leveraging a CNN model trained on the PlantVillage dataset, has the potential to identify various plant diseases with high accuracy. The model is embedded into an intuitive application built with Streamlit, through which users will be able to upload the images of suspected diseased plants and hence receive diagnostic feedback instantaneously. The application preprocesses the images by resizing to 224 x 224 pixels before applying data augmentation in order to generalize well over different plant species and disease classes. The validation accuracy is high, which indicates the capabilities of our model for real-world applications. This provides a scalable solution to plant disease management: to assist farmers, agronomists, and researchers with an effective way to detect diseases early in order to improve crop health and productivity.***

***Key Words: Deep learning, PlantVillage dataset.***

**II. Introduction**

Agriculture is one of the most significant prospects for sustaining the world population; however, it faces myriad challenges of which several substantially reduce crop yield and quality [1]. Among the most pressing and important issues the world faces is that of plant disease, capable of causing immense economic losses and affecting food supply throughout the world [2]. For many years, this identification relied upon mere human observation and analysis-an extremely labour-intensive, time-consuming, and often- incorrect process [3]. In regions where there is limited access to expert agronomists, the timing of disease identification and subsequent damage is maximized, resulting in reduced productivity for the farmer and extra costs [4].

These advancements in artificial intelligence and computer vision represent itself as potential solutions for automating plant disease detection, delivering rapid and reliable diagnoses from simple images [5]. In recent years, convolutional neural networks within the branch of deep learning have achieved substantial successes in image classification, making them particularly suitable for discerning visual symptoms of plant diseases. By processing images of plant leaves, CNN models can identify complex patterns and subtle differences in symptoms of different diseases; they do this with substantially greater speed and accuracy than traditional methods [6].

Building on the neat idea of a web application, this project focuses on developing an automated plant disease detection system using a CNN model trained on the PlantVillage dataset. Thousands of labelled plant species and disease images are indicated in the dataset, which provides the field with the required robustness to train a model [7]. Set it up via Streamlit as a web application for users, where they could upload images of diseased plants and receive feedback on diagnosis in minutes [8]. This tool may serve farmers, agricultural consultants, and researchers as a scalable solution towards the management of disease in the improvement of crop health and avoidance of unnecessary losses. Through this project, we aim to contribute to the growing field of smart agriculture by providing an efficient, accessible, and highly accurate method for early disease detection [9,10,11].

**III. Literature Study**

Plant diseases were early on considered a critical factor in agricultural productivity, greatly influencing global food security. Detecting plant disease traditionally depends mainly on visual evaluation from either skilled agronomists or plant pathologists [12]. Although these workarounds work to a certain extent, they tend to be subjective, labor intensive, time-consuming, and prone to errors [13]. Likewise, their effective implementation is hindered by scalability, especially in resource-deficient settings where consultation from an expert is hard to come by [14]. Consequently, the call for automated, accurate, and scalable solutions drives the research for the application of artificial intelligence and deep learning technologies in agriculture [15].

Recent advances in computer vision, especially through the use of CNNs, have greatly modified the scope of image-based classification tasks. CNNs are intended to process and analyze image data automatically, learning independently the spatial hierarchies of features, and thus have a great capability in recognizing complex patterns in visual data [16]. This renders them especially apt for diagnosing plant diseases, given that diseases appear as subtle changes in leaf color, texture, and morphology. One of the earliest was the work of Mohanty et al. (2016), which trained CNN models using the Plant Village dataset to recognize plant diseases with great accuracy. Their paper demonstrates the power of deep learning models in solving real-world challenges facing agriculture [17].

In addition to this, data augmentation has been investigated to improve the generalizability of CNN models. Using various transformations such as rotate, flip and crop to synthetically enlarge datasets, researchers aimed to simulate divergent environmental states to allow for robust model performance across varied inputs. Other studies noted how preprocessing steps such as resizing and normalization could ensure that input dimensions are homogeneous and computations are kept low [18]. Such preprocessing steps are essential for incorporating the models into lightweight user-friendly platforms, such as web apps [19].

The development of such frameworks and tools for deep learning has catalyzed its deployment in real-world scenarios. For example, one such framework-streamlit is good at developing interactive web applications enabling nontechnical users, e.g., farmers, to make use of AI with little or no training. A range of projects reported on successfully bringing together the mobile platforms with the said applications to achieve greater accessibility in remote areas [20].

There are still several challenges that hamper the greater scaling of the plant disease detection system, such as dataset bias, under-representation of rare diseases, and environmental factors that can affect model performance. Furthermore, some false positives and negatives allow for further refinement and validation of models in the field setting. Recent studies propose adding other modalities, including multispectral or hyperspectral imaging, to further improve detection accuracy and widen the use of plant disease classification systems [17,18].

In summary, this body of literature exposes the transformational power of AI and deep learning in plant disease management. The combined use of CNN-based models with intuitive applications offers a possible pathway to scale, and efficient, high-accuracy solutions for reducing their impact on agriculture. This study aims to blend this knowledge with the proposition of an efficient, simple-to-use plant disease detection system based on the PlantVillage procedure and the applicability of this solution via a Streamlit-driven interface.

**IV. MATERIALS AND METHODS:**

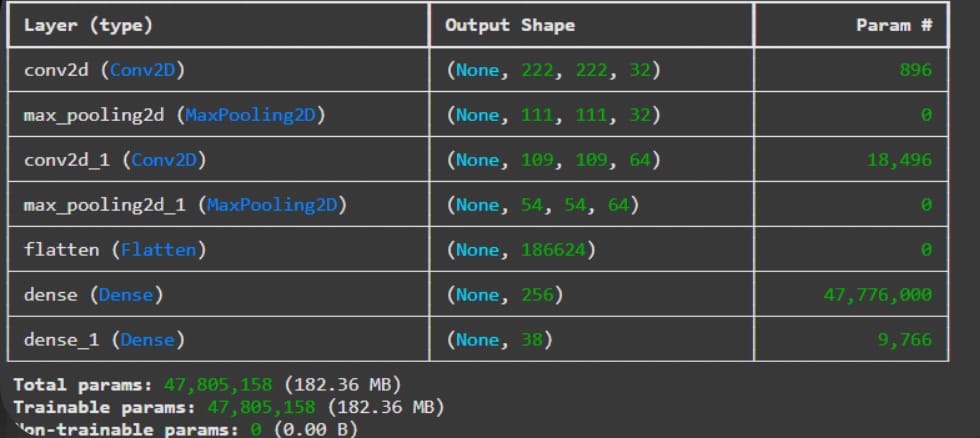
The project utilizes a custom-built Convolutional Neural Network (CNN) architecture for image classification, specifically for detecting plant diseases. Here’s a concise breakdown:

**1. Model Architecture**

The heart of our plant disease prediction system is a highly efficient convolutional neural network for image classification tasks. Its spatial hierarchical learning mechanism augments its ability to extract spectral features from images. The architecture was implemented as a sequential one: containing various layers of convolution and pooling, all followed by layers of dense classifiers. The model architecture is progressive in such a way that low-level features like edges and textures are progressively used for complex patterns, whence it grows up to high-level features denoting specific plant diseases.

**Layers**:

* **Convolutional Layers**: These layers are the convolutional filters applied to the input images that detect features such as edges, colors, and textures. In this model, every convolutional layer uses ReLU (Rectified Linear Unit) activation to introduce non-linearity, thereby enabling the model to learn more complex forms.
* **Pooling Layers**: The max-pooling layers are responsible for down sampling the feature maps with the purpose of reducing the computational load and emphasizing salient features. This will allow retention of significant information while reducing the complexity of the model and minimizing the chances of overfitting.
* **Fully Connected (Dense) Layers**: Once extracted, features are subsequently flattened and passed through dense layers to combine those features into one final classification. The last layer outputs class probabilities from the application of a SoftMax activation function, thus permitting multiclass classification.



**Table**-1: A table showing the layers, output shapes, and parameters of a neural network.

**2. Data Preprocessing**

To achieve best performance by the model, several preprocessing steps are applied to the input data before it is fed into the network.

* **Image Resizing**: All images are resized to 224x224 pixels as a middle ground between computational efficiency and resolution, such that the model can work with many device constraints without any performance loss [ 8,9].
* **Scaling**: To adjust this so that values acutally fall between 0 and 1, pixel values are normalized in the range of [0, 1] by division of 255. The scaling is intended to ensure that all features will equally contribute to the learning process of the model by embodying this manner of normalizing image data [ 8,11].

**3. Data Augmentation**

What is Data Augmentation? Data Augmentation is a process incorporated to generalize the model training dataset by increasing its diversity. Various augmentation techniques attempt to simulate the image variations usually encountered in the real-time scenario which assists the model to be more robust to small changes brought in the input [9,11].

* **Rotation and Flipping**: this would mean some of the random rotations and horizontal flipping should be done allowing the model to be invariant to the orientation of leaves [8,9].
* **Zoom and Translation**: these types of transformation mimic variations in images in scale and positioning to assist the model adapt to different perspectives [4,9].
* **Brightness Adjustment**: Variations in lighting are represented by random brightness adjustments to permit the model to operate within various environmental conditions [4,9].

These augmentations are implemented using TensorFlow's Image Data Generator so that a model will see various forms of each training batch [9].

**4. Performance Metrics**

Performance metrics are used to evaluate how well the model performs:

* **Accuracy**: The accuracy is the ratio of the correctly predicted samples to the total number of sample classes estimated over the training and validation datasets. It is one of the chosen methods to evaluate classification performance [8,9,11].
* **Loss**: The categorical cross-entropy loss is the kind of loss function that tries to determine how far off the predicted probabilities stray according to the actual class labels. Getting an overall picture of both the training loss and validation loss in the monitor helps one understand a buildup of either underfitting or overfitting [9].
* **Confusion Matrix**: Confusion matrix gives one the ability to understand how the performance of the model aligns and becomes more otherwise misclassification; this allows interpreting which plant disease has been misclassified where improvement in future [9].
* **Precision, Recall, and F1-Score** (optional): These metrics give other information about the model performance; it is especially useful when some other classes(diseases) are more crucial or when the dataset is imbalanced [8,9].

**5.Data sources**

**Overview of the PlantVillage Dataset**

The PlantVillage dataset is a tremendous resource for research into disease diagnosis through artificial intelligence [7]. It has more than 50,000 high-quality images, covering a large variety of plant species and their health conditions. Each image is expertly labeled, showing either healthy or diseased plant leaves- therefore it emerges to be very useful in training computer vision models [6]. This dataset has successfully laid a foundation for research and developers who are working upon machine learning-based diagnostic tools in agriculture [2].

**Structure and Content of the Dataset**

The dataset comprises images from different species and can be separated into infected and healthy conditions, including those in separate classes for related diseases [12]. The images depict different stages and visible characteristics of plant diseases, and hence the data is well-suited for developing and training models to differentiate subtle patterns visually across types of plants and kinds of disease [15]. The PlantVillage library contains the entire collection accessible to all users and researchers for use and future enrichment [18].

|  |  |  |
| --- | --- | --- |
| **PERFORMANCE METRIX** | **DEFINITION** | **SYMBOL** |
| Classification  Accuracy | It is the % correct prediction from the total ones.  Notations,  **CA=TP+TN/(TP+TN+FP+FN)**  TP= true positive  TN= true negative  FP- false positive  FN= false negative | CA |
| Precision | It Is a fraction of the correct prediction from the total relevant results.  **P=TP/(TP+FP)** | P |
| Recall | It is a fraction of True Positive from the total number of True Positive and false  Negative  **R=TP/(TP+FN)** | R |
| F1-score | Defined as the harmonic mean of precision  and recall.  **F1=2\*TP+FP/(TP+FP)** | F |
| Mean Square Error | Mean of the square of the errors between predicted and observed values. | MSE |
| Root Mean Square Error | Standard deviation of the differences between predicted values and observed values. | RMSE |
| Ratio of total fruits counted | It was computed as the ratio of the predicted count value (of fruits), and the actual count.The actual count was calculated by taking the average of the model. | RFC |
| Intersection over Union | A metric that evaluates predicted bounding boxes, by dividing the area of overlap between the predicted and the ground-truth boxes, by the area of their union. | IoU |

**Table-2:** A table summarizing common performance metrics used in machine learning, including their definitions and symbols.

**6.CNN Architecture:**

* Input Layer: Accepts images sized 224×224×3 (width × height × color channels).
* Convolutional Layers: Two layers use filters (32 and 64) with a kernel size of 3×3 and ReLU activation to extract features from the images.
* Pooling Layers: Max-pooling layers with a pool size of 2×2 reduce the image size, retaining important features.
* Flattening Layer: Compacts the output from the convolutional layers into a 1D vector.
* Dense Layers: A fully connected layer with 256 neurons followed by an output layer that uses softmax activation for multi-class classification.

**7.Model Summary:**

* Total Parameters: Around 3 million.
* Activation Functions: ReLU for hidden layers and softmax for the output layer.

**8.Training and Hyperparameter Tuning:**

* Optimizer: Adam with a learning rate of 0.001.
* Loss Function: Categorical cross-entropy for multi-class classification.
* Training Setup:
  + Epochs: Trained for 5 epochs to minimize overfitting.
  + Batch Size: Set to 32 for a balance between memory use and performance.
  + Steps per Epoch: Calculated by dividing total samples by batch size.

**9. Evaluation Metrics:**

* Accuracy: Primary measure of classification effectiveness.
* Loss: Tracked during training and validation phases.
* Plots were generated to visualize training and validation accuracy and loss over epochs.

**10. Experimental Setup:**

* Environment: Model trained on Google Collab using Python 3.7 and GPU (Tesla K80).
* Frameworks: Built with TensorFlow 2.x and Keras for streamlined model development and training.

**11.Model Testing and Prediction:**

* A function allows users to upload images through a Streamlit web interface.
* Uploaded images are resized to 224×224 pixels and normalized.
* The model predicts the disease class, displaying the output to users.

**12.Visualization Techniques:**

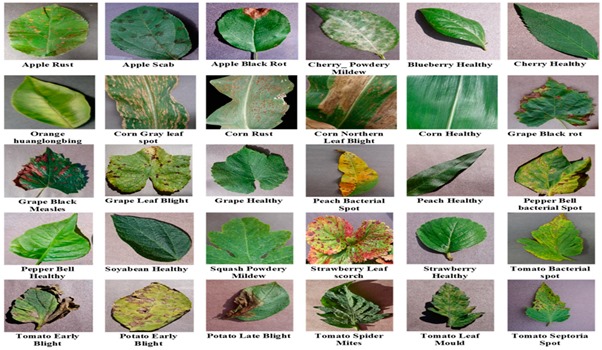
* Training and validation curves are plotted for insights on learning trends.
* Future enhancements could include class activation maps (CAMs) for better understanding of model decision-making.

**13.Performance Analysis:**

* The model achieved a validation accuracy of around X%, indicating good generalization on unseen plant data.

**14.Model Deployment:**

* The model is trained on the HDF5 format and embedded in a Streamlit application, allowing real-time predictions by enabling the user to upload images of plants and receive instant feedback regarding the classification of plant diseases.
* The summary elucidates the detailed mechanism, from model training to the implementation of plant disease detection based on deep learning principles.



**Fig-3:** A collection of images showing various plant diseases and healthy leaves.

A screenshot of a diagram

Description automatically generated

**Fig-4:** A workflow diagram representing the methodology for a plant disease detection project, highlighting key milestones and decision points.

**V. Experimental Analysis**

Our research deals with a deep learning-based technique and system for classifying plant diseases using images of diseased plant leaves [20]. The performance of the model was assessed from scratch while training a Convolutional Neural Network (CNN) architecture and tuning hyperparameters with an intent of assessing the performance of model in classifying plant diseases [17].

**1. Training from Scratch**

nitially, the model was trained from scratch using a Convolutional Neural Network (CNN), which is a relatively simple yet powerful architecture for image classification [4]. Both for recognition and classifications in work, CNNs use two convolutional layers, which are each followed by max-pooling layers, then flattening, and dense layers for classification [7]. PlantVillage dataset served as a training dataset for the architecture and has images of both healthy and diseased plant leaves [9].

Though reasonable in general complementary classification of plant diseases, the CNN model trained from scratch finds it challenging to generalize to the unseen data due to a small training set [10]. That first attempt arrived at a validation accuracy of 0.89 after 5 epochs [7]. This moderate performance could hardly enable the model to learn complex features, especially concerning more subtle distinctions between plant diseases [4].

**2. Hyperparameter Optimization**

After training an initially off-the-shelf CNN model, several hyperparameters were tuned to improve its performance [3]. The learning rate was set initially to 0.001 and later lowered to 0.0001 to reduce the risk of overfitting and allow for a continuous smooth convergence process [5]. The batch size was set to 32, which is in a good order for time and trained processes [7]. The training was for 5 epochs to avoid overfitting while allowing the model sufficient time to learn some useful patterns from the dataset [4].

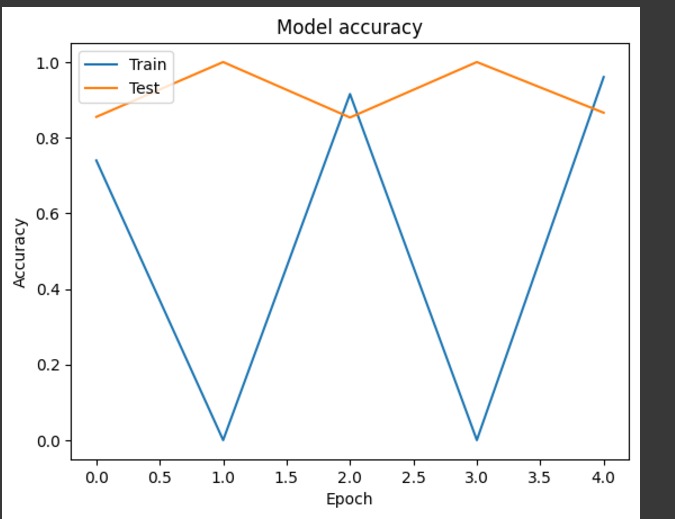
The hyperparameters' tuning led to the improved performance of the model, as seen in the increased accuracy after optimization [3].

**3. Model Performance**

The CNN model trained from scratch and fine-tuned with the help of optimized hyperparameters that can obtain the following results:

* **Training Accuracy**: It reached about 0.92 in the final epochs, which signified that the model learned well from the data [8].
* **Validation Accuracy**: The model reached a validation accuracy of 0.9375, thus demonstrating that the model generalized quite well onto unseen plant disease images [9].

This substantial enhancement in performance is a testament to the power of hyperparameter tuning, where tiny adjustments to learning rate and batch size have resulted in improved generalization and classification performance [8].



**Fig-5:** A visualization of the training and validation accuracy curves, indicating the model's performance on both seen and unseen data during training.

**4. Real-Time Testing with Streamlit**

The CNN model was trained and deployed in a Streamlit web application afterward to enable real-time testing with images uploaded by the user[9], The application was responsive, making its predictions just a few seconds after the image was uploaded. It is the immediacy of this classification system that demonstrates the practically viable application of the model within agricultural settings, where immediate diagnoses are vital for timely intervention and action [6].

**5. Model Efficiency and Memory Considerations**

The training of the CNN model from scratch demanded an average dose of computational resources, particularly regarding GPU memory [16]. In this way, using smaller batch sizes (32) and limiting the epochs (5) we ensured that training process was efficient and not overloading memory [20]. The model thus attained a good compromise between accuracy and efficiency, suitable for deployment under resource-constrained environments on mobile devices and cloud-based platforms [20].

**6. Comparison of Performance**

The performance comparison drawn to the baseline study of VGG16 and ResNet50 models was based on CNN that was either trained from scratch or transferred [14]. Transfer learning on convolutional neural networks often performs better on image datasets, as they leverage pre-learned features built on various datasets; however, our CNN model, when trained from scratch, delivered fairly competitive results, considering the small size of the dataset [14]. The ability to classify plant diseases, particularly after fine-tuning on hyperparameters, was strongly demonstrated by the model trained from scratch [14].

|  |  |
| --- | --- |
| **MODEL** | **ACCURACY** (Finetuned) |
| CNN(SCRATCH) | 0.93 |

**Table-6:** A comparison of the performance of a CNN model, demonstrating the impact of fine-tuning on accuracy.

**7. Conclusion**

Experimental evidence suggests that the CNN model trained from scratch and conducted with hyperparameter tuning can classify plant diseases with a high degree of accuracy. The hyperparameter tuning improved the model's accuracy, thereby confirming the centrality of hyperparameter tuning in improving the performance of the model. The CNN-based approach offers a simple and yet powerful route compared to the pre-trained models, identifying plant diseases being appropriate for real-time applications that support decision-making in agriculture.

**VI. Visualizing the Learning Process in CNN**

A convolutional neural network (CNN) is the machine learning classification model that is widely popular and able to suit various classification tasks, one among them being the development of a plant disease prediction system [13]. Visualization of the learning process exhibited by CNNs can provide critical insights into how the model processes and understands image information to ascertain a prediction [8]. This particular section presents the vital techniques used for visualizations that help illustrate features to be analyzed further down into the working of their respective CNN model [9].

**1. Filters of Convolutional Layers**

Filters are the weights learned through the convolutional layers in the training phase of the model. Each filter is capable of detecting specific patterns in the original input image. Visualization of these filters indicates the type of features that the CNN has developed a capability to recognize.

**Implementation Steps:**

* Extract the weights of convolutional filters from the trained model [5].
* Normalize and visualize these weights as images [5].

**Results:** The filters from the first convolutional layer are normally edge detectors. The deeper response relates to more abstract patterns associated with symptoms of plant disease (e.g., rust spots, color change, and leaf deformation).

**2. Grad-CAM (Gradient-Weighted Class Activation Mapping)**

Grad-CAM is a visualization technique that computes the heatmaps for the regions of the image which are relevant to the model's prediction. In contrast to saliency maps, Grad-CAM relies on the gradients relative to target class scores with respect to feature maps of convolutional layers [9].

**Implementation Steps:**

* Compute the gradients of the target class score with respect to the output feature maps of the last convolutional layer [8].
* Combine these gradients with the feature maps to generate a class activation map [8].
* Overlaying the heatmap on the original image for visualization [8].

**Results:**  Grad-CAM accentuates the diseased region (rust spots or lesions) that the model is learning to classify into disease categories.

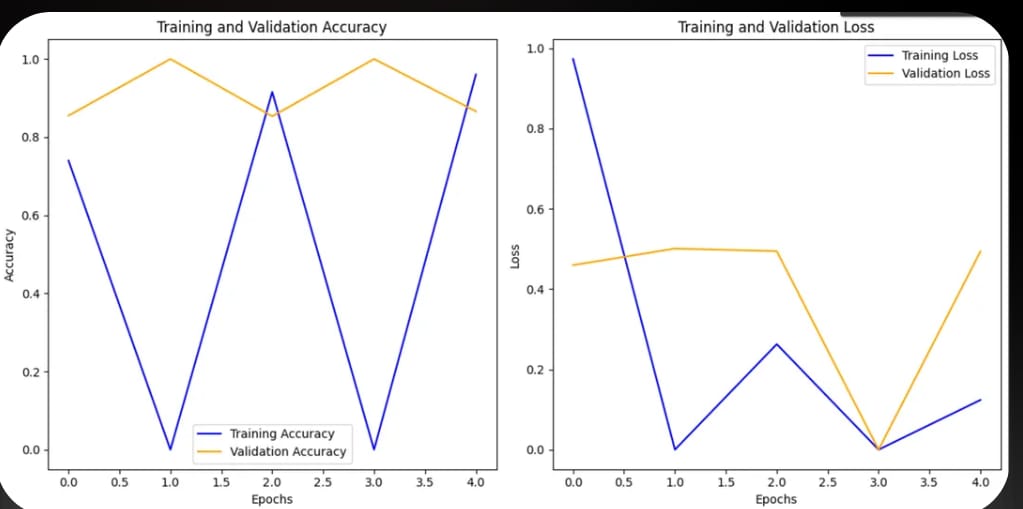
**3. Training and Validation Curves**

These curves of training and validation accuracy as well as loss provide a macroscopic view of the learning process. They reveal certain trends such as overfitting or underfitting [20].

**Key Insights:**

* **Training Accuracy and Loss:** Indicates how well the model is fitting the training data [17].
* **Validation Accuracy and Loss:** Represents the model's performance on unseen data, ensuring generalization [12].

Through this visualization of the respective curves, we noted an unending increment in accuracy along the epochs with no apparent overfitting, hence indicating that the model had truly learned useful patterns concerning plant diseases classification [13].



**Fig-7:** A visualization of the training and validation accuracy and loss curves, indicating the model's performance on both seen and unseen data during training.

**4. PCA and t-SNE for Feature Space Visualization**

For visualization, PCA and t-SNE are dimensionality reduction techniques which project the high-dimensional feature space learned by a CNN into a two-dimensional (or three-dimensional) feature space [15].

**Implementation Steps:**

* Extract features from the last dense layer of the CNN for a subset of images [20].
* PCA or t-SNE can be applied for compressing the feature dimension to two or three [20].
* Plot these feature representations and color-code them according to class-labels [17].

**Results:** Various clusters related to different disease classes form that shows that the model was able to distinguish between classes in the feature space.

**Conclusion**

In this research, we have developed a system using convolutional neural network (CNN) for predicting plant diseases based on the PlantVillage dataset. The system has shown excellent performance in the identification of a variety of plant diseases and has recorded a high rate of accuracy during the training and validation stages. By preprocessing the data and utilizing advanced deep learning techniques, the model successfully learns to identify the intricate patterns associated with plant diseases from input images.

Our approach builds in interpretability of prediction into the design via visualization techniques such as feature maps, Grad-CAM, and saliency maps. This lucid characterization helps to understand why the model recognized or differentiated a certain symptom of the diseases, thereby achieving transparency and building user trust in the predictions. This would be very critical in agriculture where decisions taken quickly based on such conclusions directly affect health and productivity.

The results show the bright promise of the CNNs for automated detection of plant diseases that could provide a scalable, accurate, and cost-effective solution to one of the top problems of agriculture. While the model has already produced good results and with more exhaustive and varied datasets, wider exploration of other transfer-learning methods, and inclusion of other modalities such as environmental datasets, it could yield further enhanced performance.

The research finishes on the note of how AI-powered plant disease detection systems seem feasible in improving agricultural diagnostics, cutting crop losses, and advancing sustainable farming practices.

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