Methodology

Classical ML Approach (Random Forest)

1. **Feature Extraction**: Images were processed to extract numerical features.
    - **Color Histograms**: Calculated for RGB channels to capture color distribution
    - **Haralick Texture Features**: Computed from grayscale images to represent texture properties
2. **Data Preprocessing**:
    - All extracted features were stacked into a single feature vector for each image.
    - Features were **standardized** to ensure all features contribute equally to the model.
3. **Model Selection**: A **Random Forest Classifier** with 100 estimators was chosen for classification.
4. **Training and Evaluation**:
    - The dataset was split into **80% training and 20% testing** sets, with stratification to maintain class proportions.
    - The model was trained on the training data and evaluated on the test set.
    - **Confusion Matrix**, **Classification Report**, and **Accuracy Score** were generated.
    - **5-fold Cross-Validation** was performed to assess model generalization.
    - **Feature Importance** was calculated and visualized for the Random Forest model.

Deep Learning Approach (ResNet18)

1. **Data Preprocessing (Transforms)**: Images were transformed for input into a deep learning model.
    - **ToTensor**: Converted images to PyTorch tensors.
    - **Normalization**: Pixel values were normalized using ImageNet's mean and standard deviation.
2. **Dataset and Split**:
    - The dataset was split into **80% training and 20% validation** sets.
    - **DataLoaders** were created for batching and shuffling.
3. **Model Architecture**: A **pre-trained ResNet18 model** was used.
    - The final fully connected layer of ResNet18 was replaced to match the number of output classes.
4. **Training Configuration**:

   - **Loss Function**: CrossEntropyLoss was used, suitable for multi-class classification.
   - **Optimizer**: **Adam optimizer** with a learning rate of 0.001 was chosen.
   - The model was trained for **6 epochs**.
5. **Training and Validation Loop**:
   - The model was trained in batches
   - Validation was performed after each epoch to monitor performance on unseen data.
   - **Training and Validation Loss history** was recorded.
   - **Confusion Matrix** and **Classification Report** were generated from validation predictions.

Results

Classical ML Approach (Random Forest)

- **Overall Accuracy**: The model achieved an **accuracy of 0.95 (95%)**.
- **Cross-validation Accuracy**: 0.9429±0.0123, indicating consistent performance across different data subsets.
- Confusion Matrix:
  * High true positives are observed along the diagonal. For instance, Healthy (223 out of 225 actual healthy samples were correctly classified), Downy_mildew_on_lettuce (121/121), and Shepherd_purse_weeds (194/195) show excellent performance.
  - Some misclassifications occurred:
    - **Bacterial** was sometimes misclassified as "Powdery_mildew_on_lettuce" (2) or "Septoria_blight_on_lettuce" (6).
    - **Viral** was frequently misclassified as "Healthy" (7).
    - "Wilt_and_leaf_blight_on_lettuce" was misclassified as "Bacterial" (1), "Powdery_mildew_on_lettuce" (2), and "Septoria_blight_on_lettuce" (1).
- **Classification Report**:
  - **Healthy**, **Downy_mildew_on_lettuce**, and **Shepherd_purse_weeds** classes show very high precision, recall, and f1-score (all close to 0.99 or 1.00), indicating robust performance for these classes.
  - Classes like **Bacterial**, **Powdery_mildew_on_lettuce**, and **Septoria_blight_on_lettuce** have good precision/recall but slightly lower F1-scores compared to the best-performing classes.
  - **Viral** has good recall (0.89) but slightly lower precision (0.85).
  - "Wilt_and_leaf_blight_on_lettuce" shows perfect precision (1.00) and recall (1.00), but with only 25 samples.

Deep Learning Approach (ResNet18)

- **Training Progress**:
    - **Loss over Epochs**: Both training and validation loss generally decreased over 6 epochs, indicating learning. Training loss decreased from around 1.2 to below 0.2, while validation loss decreased from around 0.8 to around 0.1.
    - **Accuracy (Approximate)**: The validation accuracy, approximated from validation loss, steadily increased, reaching over 0.8 by epoch 2 and fluctuating around 0.8-0.9 in later epochs.
- Confusion Matrix:
  * Excellent performance is seen for Healthy (241/242), Downy_mildew_on_lettuce (136/136), and Shepherd_purse_weeds (193/193).
    - Some misclassifications:
        - **Powdery_mildew_on_lettuce** had 3 samples misclassified as "Downy_mildew_on_lettuce" and 1 as "Healthy."
        - **Viral** had 4 misclassified as "Downy_mildew_on_lettuce."
        - **Wilt_and_leaf_blight_on_lettuce** had 1 misclassified as "Shepherd_purse_weeds."
- **Classification Report**:
    - Similar to the classical approach, **Healthy**, **Downy_mildew_on_lettuce**, and **Shepherd_purse_weeds** show outstanding precision, recall, and f1-scores (all near 1.00).
    - **Bacterial**, **Septoria_blight_on_lettuce**, and **Viral** also show strong performance (F1-scores > 0.90).
    - **Powdery_mildew_on_lettuce** has a precision of 0.95 and recall of 0.92, indicating good but not perfect performance.
    - **Wilt_and_leaf_blight_on_lettuce** shows very good precision and recall (0.96 and 1.00, respectively).

Observations

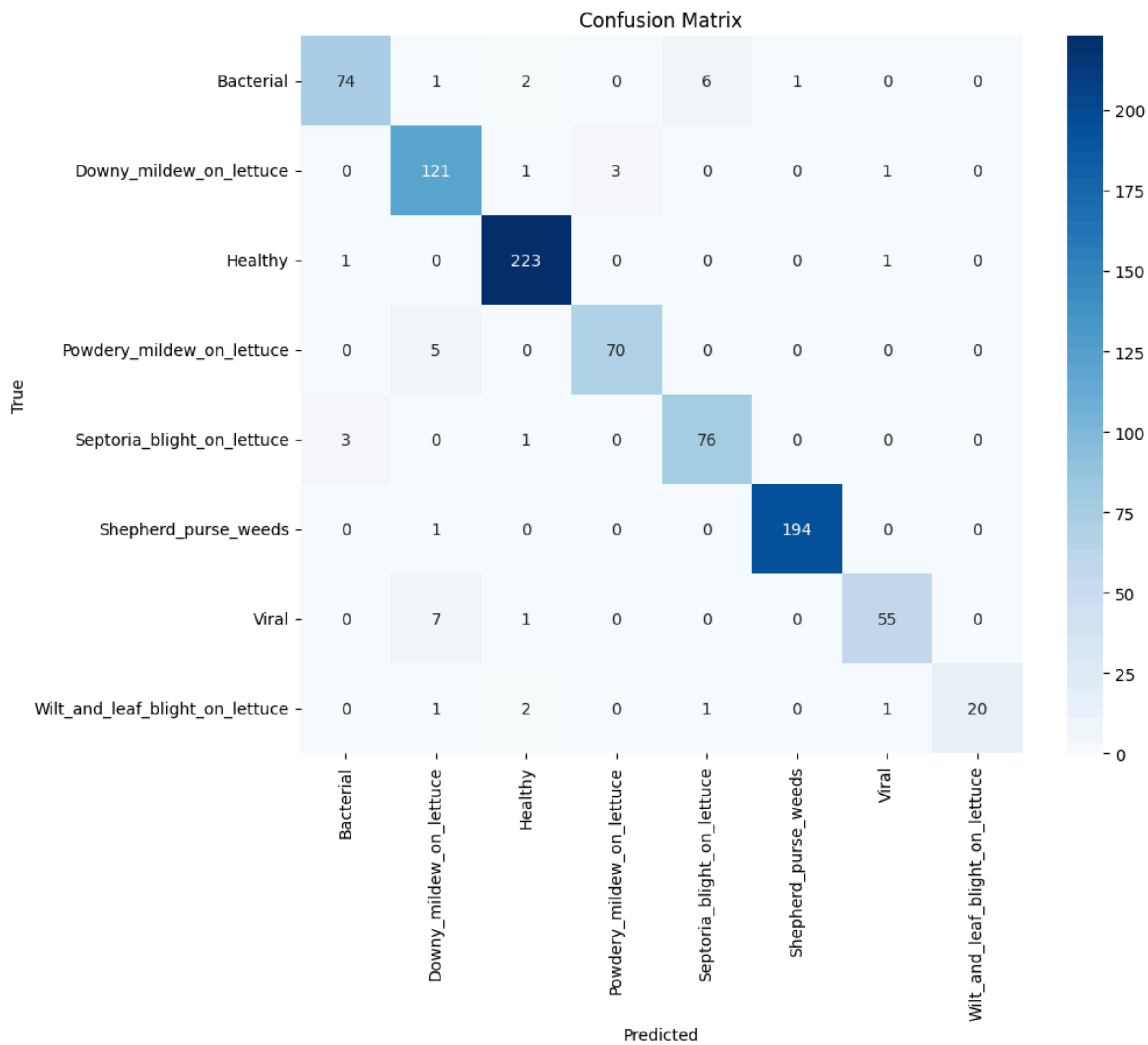
Both classical machine learning with **Random Forest** and the **Deep Learning approach with ResNet18** achieved high accuracy in classifying plant diseases.

- The **Random Forest model** achieved an overall accuracy of **95%** with a cross-validation accuracy of 94.29±1.23%. It demonstrated strong performance across most classes, particularly for "Healthy," "Downy_mildew_on_lettuce," and "Shepherd_purse_weeds." However, some misclassifications occurred, notably "Viral" being confused with "Healthy" in some instances.
- The **Deep Learning model (ResNet18)** also showed excellent performance, with training and validation losses decreasing effectively over epochs. The confusion matrix indicates very high accuracy across several classes, with only a few misclassifications. It seems to handle the nuances of visual features effectively due to its pre-trained nature and convolutional capabilities.

- Comparing the confusion matrices both models show similar patterns of strong performance for well-represented and distinct classes. The deep learning model appears to have slightly fewer scattered misclassifications for some classes (e.g., "Powdery_mildew_on_lettuce" and "Wilt_and_leaf_blight_on_lettuce" have fewer misclassifications to diverse classes in the DL approach).
- The deep learning model's training process, as visualized by the loss and approximate accuracy plots, shows a stable learning curve, suggesting good model convergence.
- The use of **pre-trained models** in the deep learning approach likely contributed significantly to its high performance, as these models have learned rich feature representations from large datasets like ImageNet. In contrast, the classical approach relied on handcrafted features (color histograms and Haralick textures), which, while effective, might not capture the same level of complexity as learned features from a deep network.

In conclusion, both methods are highly effective for this plant disease classification task. The **Deep Learning approach with ResNet18 appears to slightly edge out the classical Random Forest model in overall robustness and handling of more complex disease patterns**, likely due to its ability to learn hierarchical features directly from raw image data.

Classical ML Approach confusion matrix:


Confusion Matrix
True
Predicted
Bacterial
Downy_mildew_on_lettuce
Healthy
Powdery_mildew_on_lettuce
Septoria_blight_on_lettuce
Shepherd_purse_weeds
Viral
Wilt_and_leaf_blight_on_lettuce
74 1 2 0 6 1 0 0
0 121 1 3 0 0 1 0
1 0 223 0 0 0 1 0
0 5 0 70 0 0 0 0
3 0 1 0 76 0 0 0
0 1 0 0 0 194 0 0
0 7 1 0 0 0 55 0
0 1 2 0 1 0 1 20
0 25 50 75 100 125 150 175 200

DeepLearning Approach confusion matrix: