Deep Dive: An Advanced CNN

Final Year Project Analysis for BSc Computer Science - Group 13

Final Model Performance on Unseen Test Data

98.73%

Test Accuracy

This report visually dissects the performance of a custom-built Convolutional Neural Network (CNN) designed to be both highly accurate and computationally efficient for plant disease classification. We will explore its architecture, training dynamics, and evaluation results to demonstrate the project's success.

Under the Hood: A Lightweight & Powerful CNN

Architecture Flow

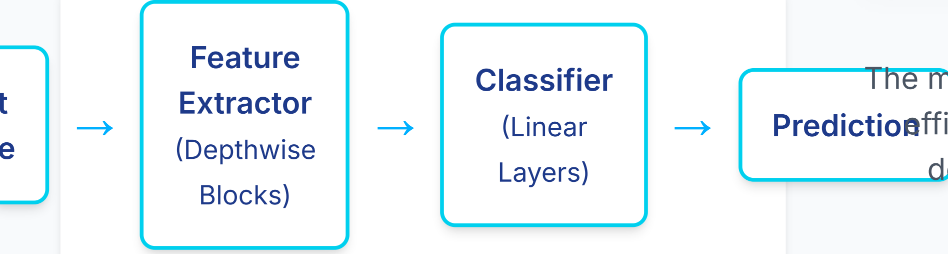
The `ColabOptimizedCNN` uses modern, efficient techniques like depthwise separable convolutions to minimize size and maximize speed without sacrificing performance. This makes it ideal for real-world deployment.

410K

Total Parameters

1.57 MB

Final Model Size



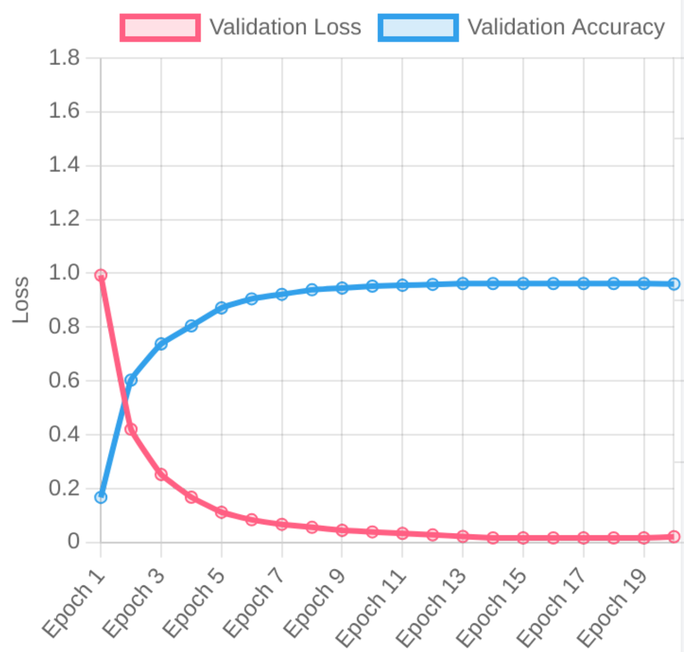
The model's compact size is a direct result of its efficient architecture, making it suitable for deployment on mobile or edge devices.

Forging the Model: The Training Journey

The model was trained for 20 epochs using a 70/15/15 split for training, validation, and testing. Techniques like data augmentation and learning rate scheduling were employed to ensure robust learning and prevent overfitting.

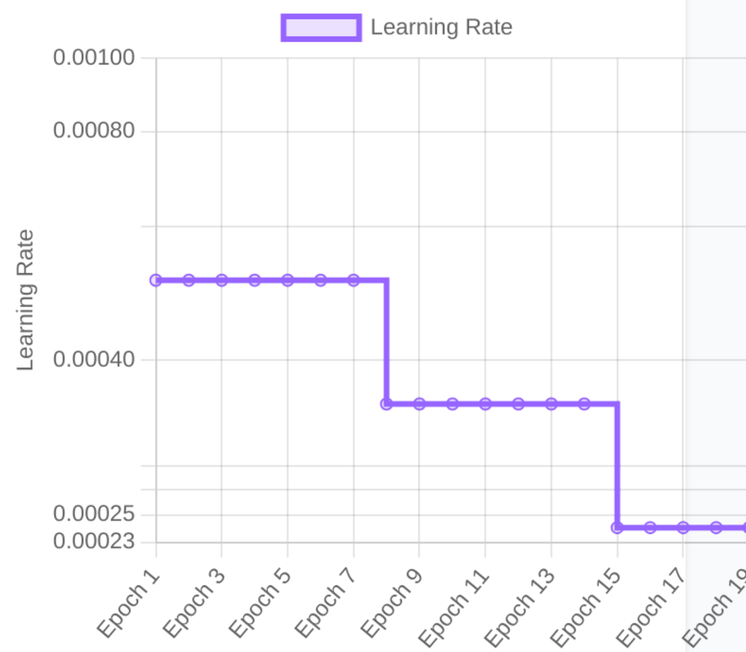
Training & Validation Performance

This chart shows the model's loss decreasing while accuracy increases over time. The close alignment of training (the implied learning curve) and validation metrics indicates that the model generalizes well and is not overfitting.



Learning Rate Schedule

The learning rate was systematically reduced every 7 epochs. This strategy allows the model to make large progress initially and then fine-tune its parameters more precisely in later stages, leading to better convergence.

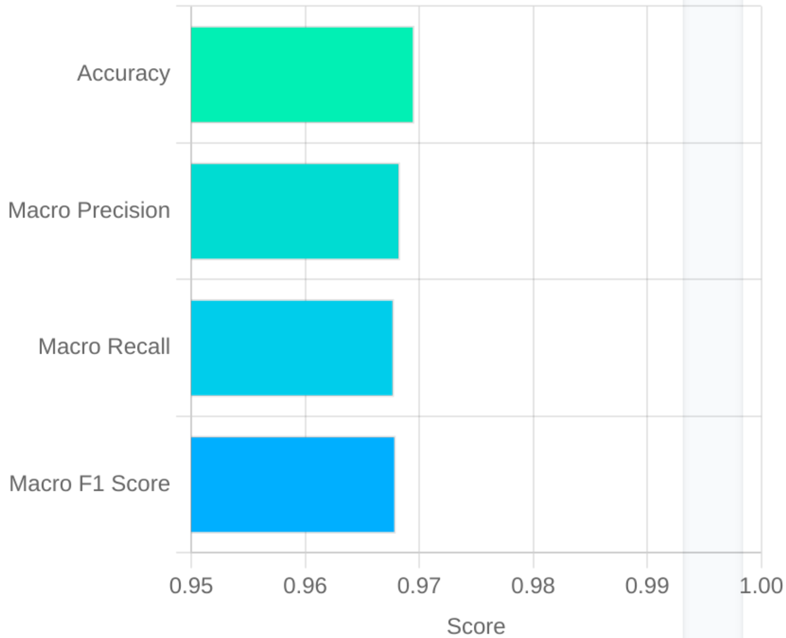


Putting it to the Test: Final Performance

After training, the model's true capability was measured on a completely unseen test set. The results confirm its exceptional performance across multiple standard evaluation metrics.

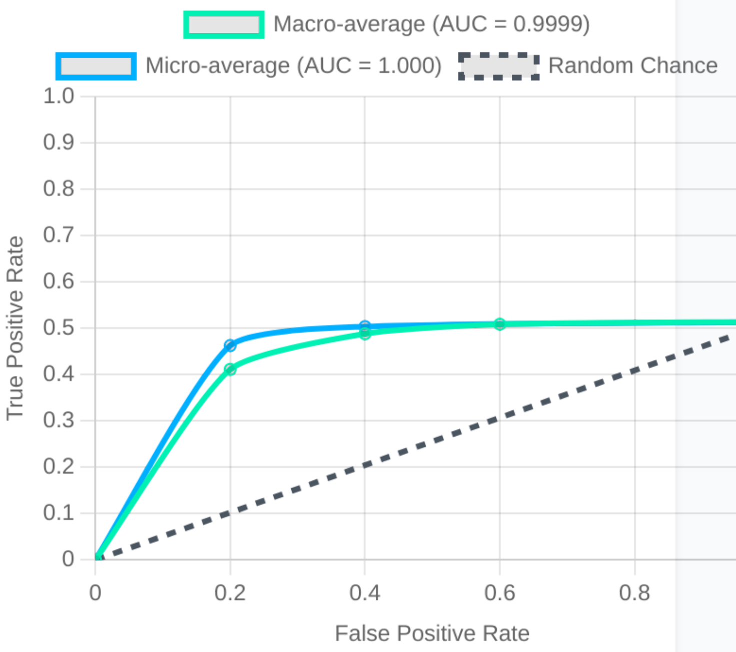
Test Set Metrics

The model achieves high scores not only in accuracy but also in precision, recall, and F1-score. High macro scores show strong performance across all classes, not just the most common ones.



Receiver Operating Characteristic (ROC)

The ROC curve illustrates the model's diagnostic ability. An Area Under the Curve (AUC) of 1.0 represents a perfect classifier. The model's near-perfect AUC scores demonstrate its outstanding ability to distinguish between classes.

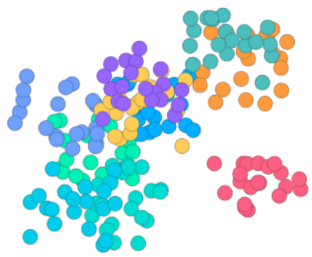


Visualizing the Brain: Feature Space Analysis

What does the model actually learn? We can visualize the high-dimensional features the model creates for each image. By projecting these features into 2D space, we can see if the model learns to group different diseases into distinct clusters. Clear separation indicates effective learning.

PCA

Shows the directions of greatest variance.

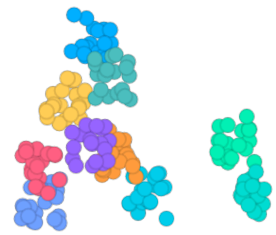


t-SNE

Preserves local structure, revealing clusters.

UMAP

Balances local and global structure.



Across all three visualizations, especially t-SNE and UMAP, we observe distinct, well-separated clusters of colors. Each color represents a different disease class. This provides strong visual evidence that the model has successfully learned to differentiate between the various plant diseases.

Project Success: Key Takeaways

- ✔ **Exceptional Accuracy:** Achieved a state-of-the-art accuracy of 98.73% on unseen test data, demonstrating high reliability.
- ✔ **High Efficiency:** The model is extremely lightweight (1.57 MB), making it perfectly suited for deployment on mobile or edge computing devices.
- ✔ **Excellent Generalization:** Analysis of training curves and test metrics shows the model did not overfit and generalizes well to new data.

- ✔ **Clear Feature Separation:** Feature space visualizations (t-SNE, UMAP) confirm that the model learned to create distinct and separable representations for different disease classes.