MACHINE LEARNING PROJECT

AI-Driven Tomato Leaf Disease Classification Using Self-Supervised CAE-CNN Framework

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SU92-MSDSW-F25-004

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Superior University, Lahore | January 30, 2026

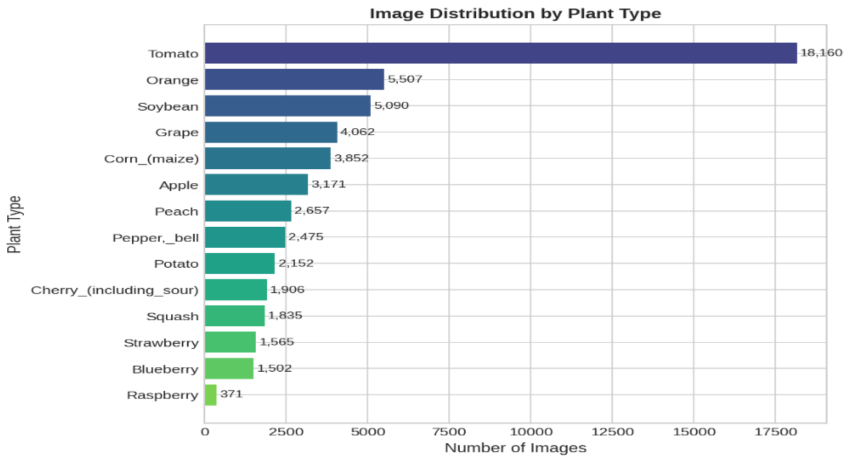
1. Introduction

The Problem: Plant diseases cause 20-40% annual crop losses globally, threatening food security

The Gap: Most deep learning models rely on ImageNet pre-training, not optimized for agricultural imagery

The Challenge: Manual diagnosis is time-consuming, requires expert pathologists, and prone to human error

Our Solution: Self-supervised CAE pre-training with two-phase CNN classification achieving 98.02% accuracy



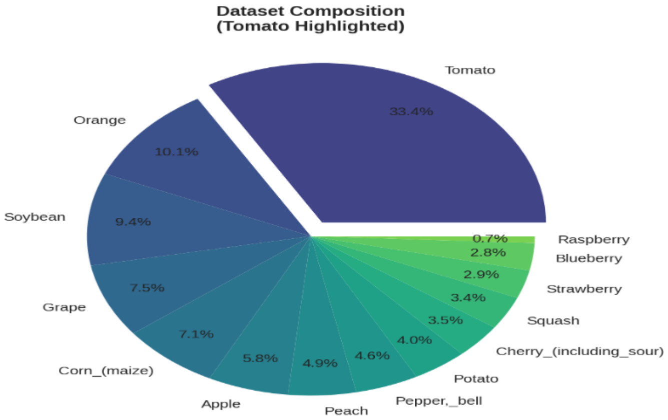


Figure 1: Dataset Composition

2. Project Objectives

Primary Objectives

1. Develop CAE-CNN achieving accuracy > 95%
2. Train without ImageNet pre-trained weights
3. Handle class imbalance (14.36x ratio)
4. Create interpretable feature representations

Technical Objectives

1. Achieve F1-Score > 0.95 across all classes
2. Implement two-phase training strategy
3. Validate with comprehensive metrics
4. Enable edge device deployment

3. Alignment with UN Sustainable Development Goals

SDG 2: Zero Hunger

- Reduces crop losses (15-25%)
- Supports sustainable agriculture
- Enables early disease intervention

SDG 9: Industry, Innovation & Infrastructure

- Applies cutting-edge deep learning
- Builds AI infrastructure
- Promotes innovation

SDG 12: Responsible Production

- Reduces pesticide use (20-30%)
- Optimizes resource allocation
- Supports precision farming

Project Impact

- Cost reduction: $200-500/hectar
- 98.02% accuracy for automated screening
- Lightweight model (16.9M params) for mobile deployment

4. Dataset: PlantVillage Tomato Subset

18,160	10	14.36x	128x128
Total Images	Disease Classes	Class Imbalance	Image Resolution

Data Split: Train 80% (14,528) | Val 10% (1,816) | Test 10% (1,816) - Stratified sampling

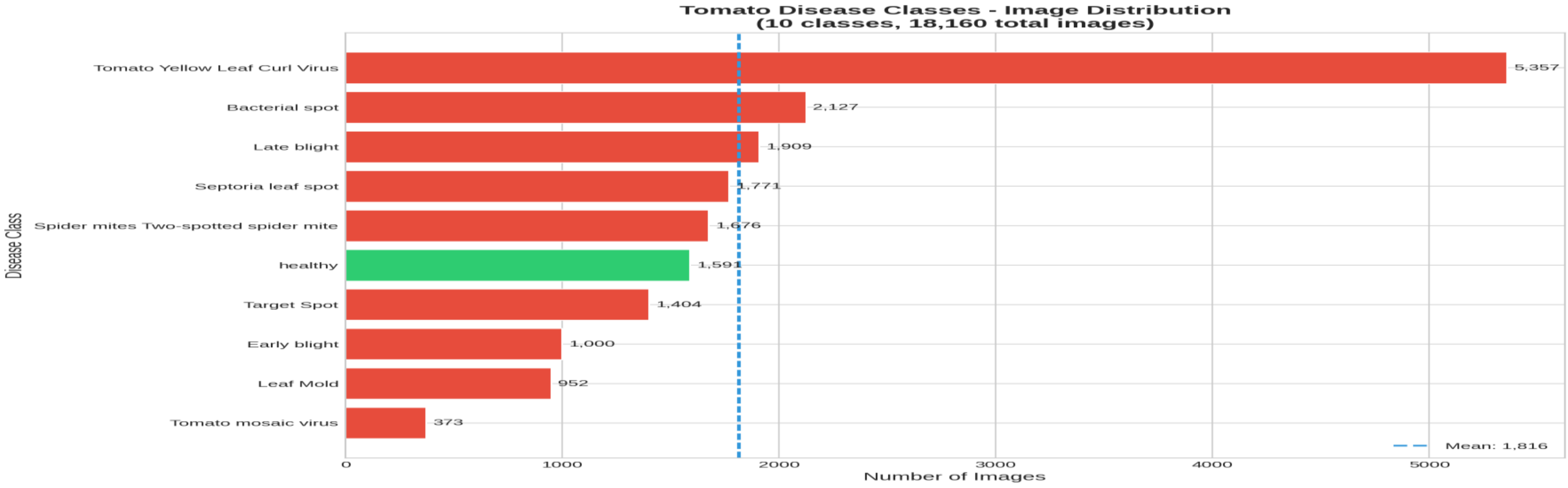


Figure 2: Class Distribution

5. Spectral Comparison (Healthy vs Diseased)

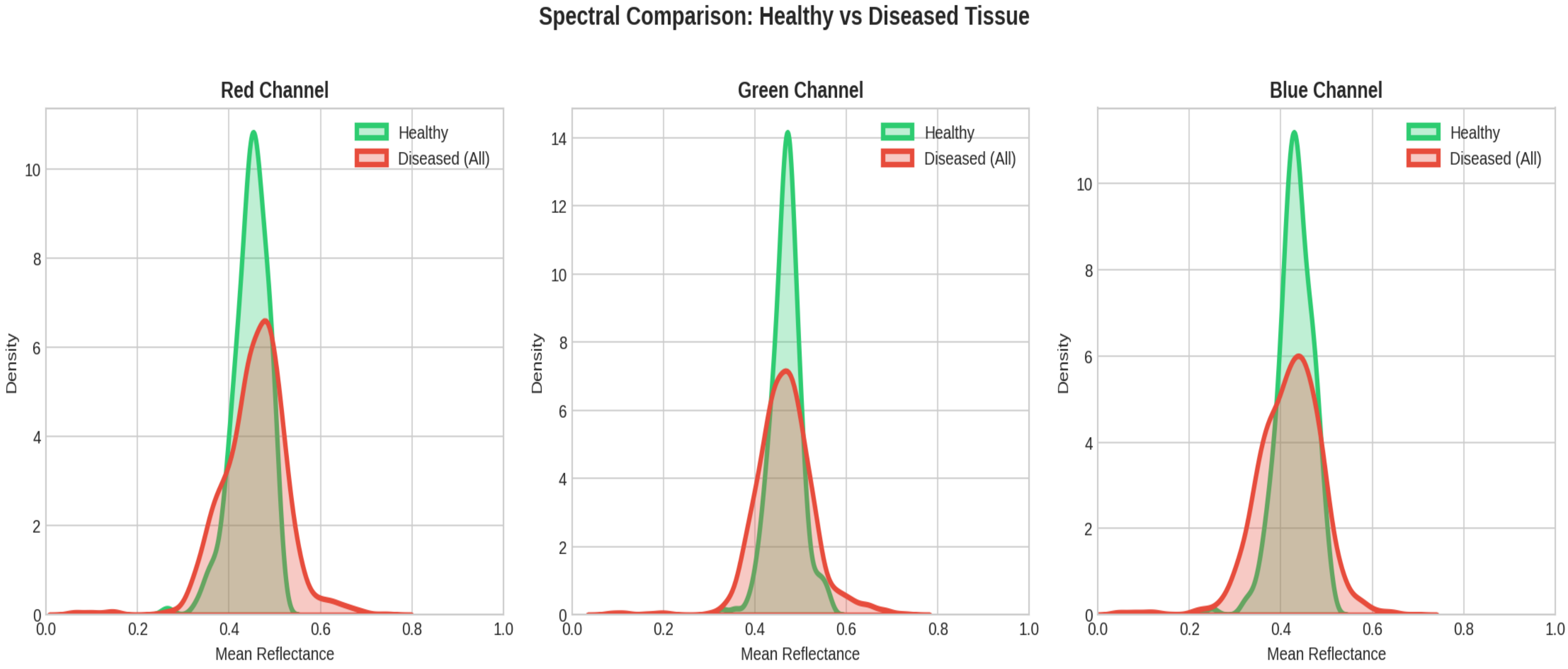


Figure 3: Spectral Comparison

6. Methodology: Project Workflow

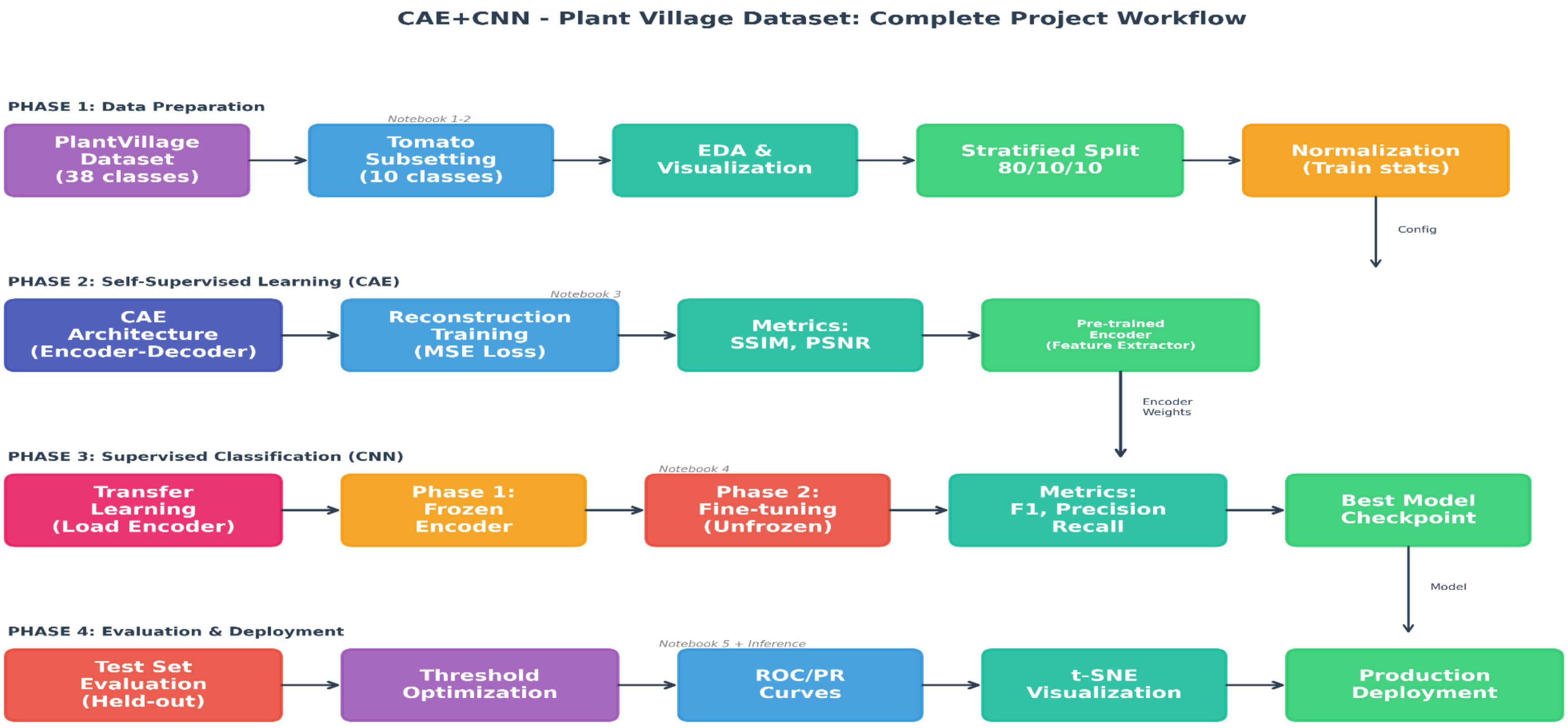


Figure 4: Project Workflow

7. Data Pipeline

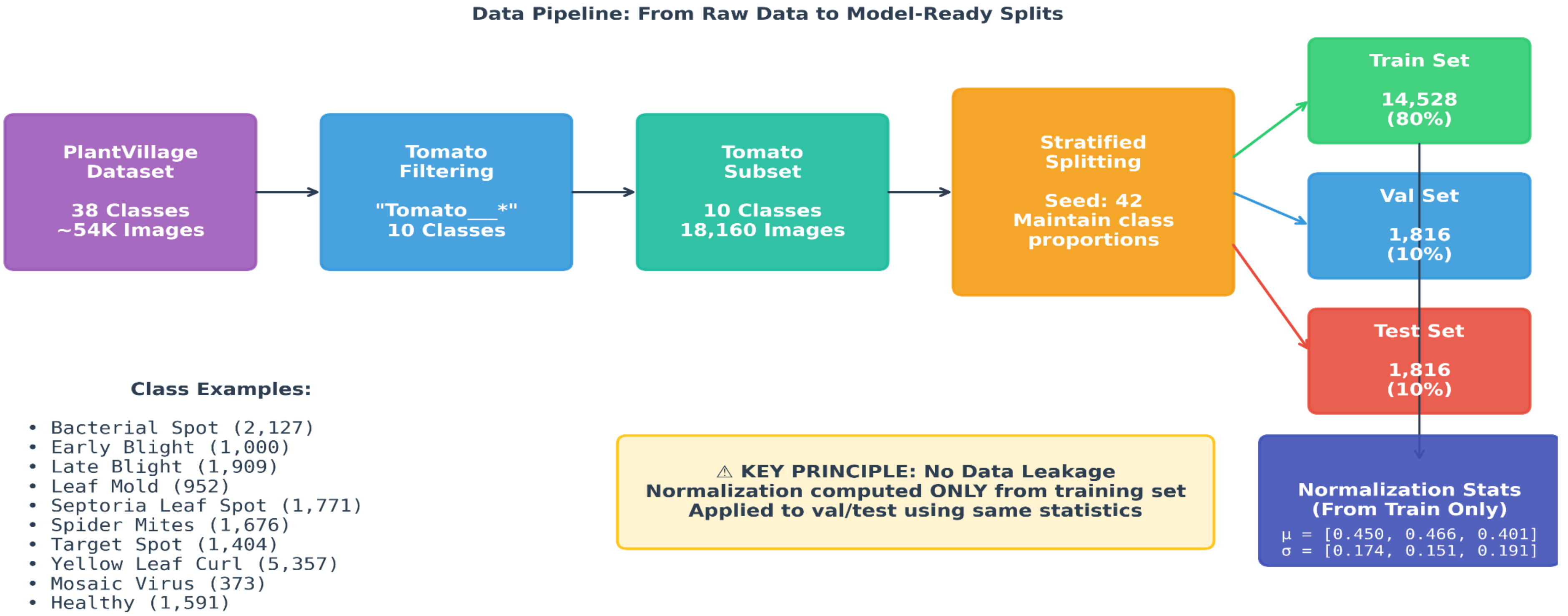


Figure 5: Data Pipeline

8. CAE Architecture: Self-Supervised Feature Learning

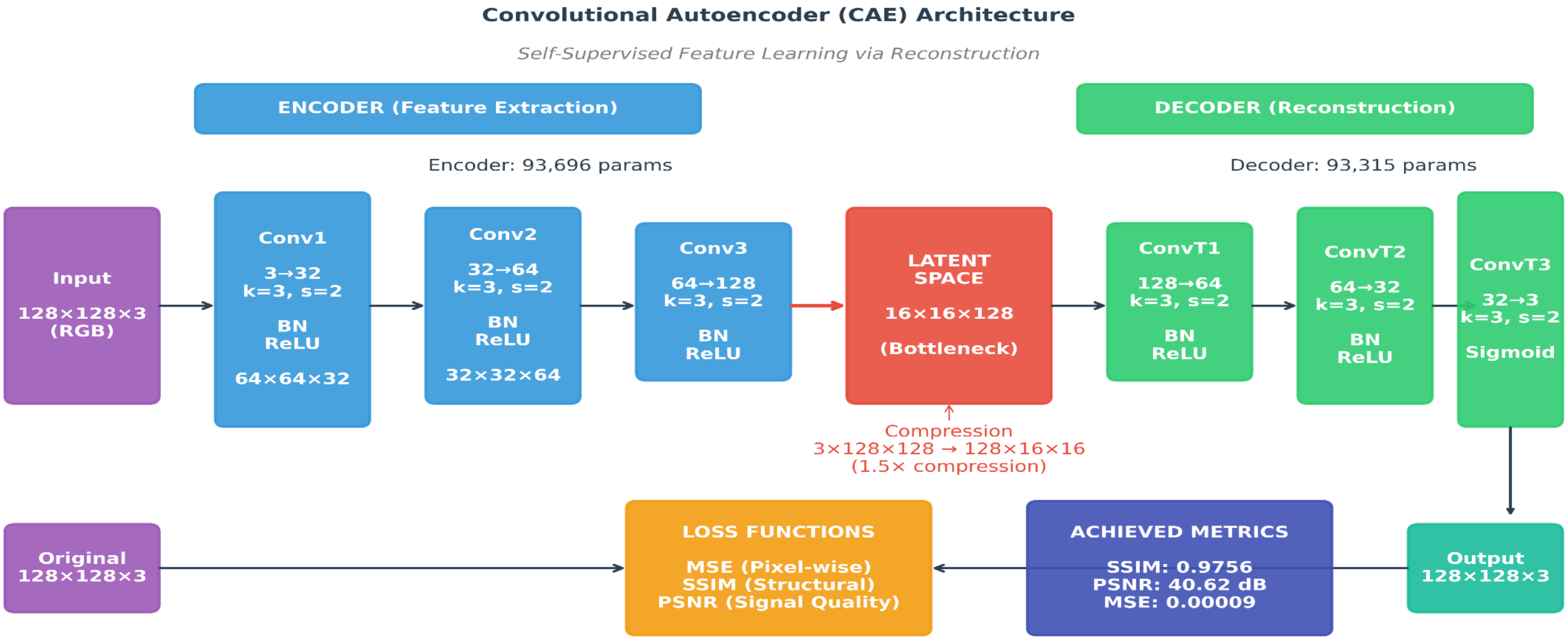


Figure 6: CAE Architecture

9. Two-Phase Training Architecture

Phase 1: Frozen Encoder

- CAE encoder frozen
- Classifier head trained
- LR: 1e-3, Epochs: 15
- F1: 0.7711

Phase 2: Fine-tuning

- All layers unfrozen
- End-to-end training
- LR: 1e-4, Epochs: 25
- F1: 0.9774 (+26.7%)

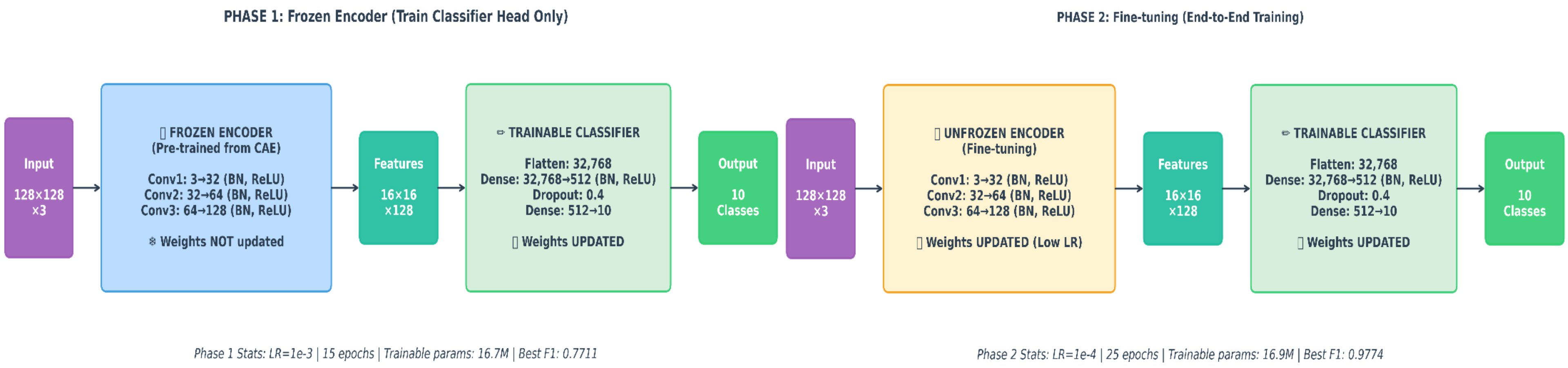


Figure 7: Two Phase Training

10. Training Pipeline

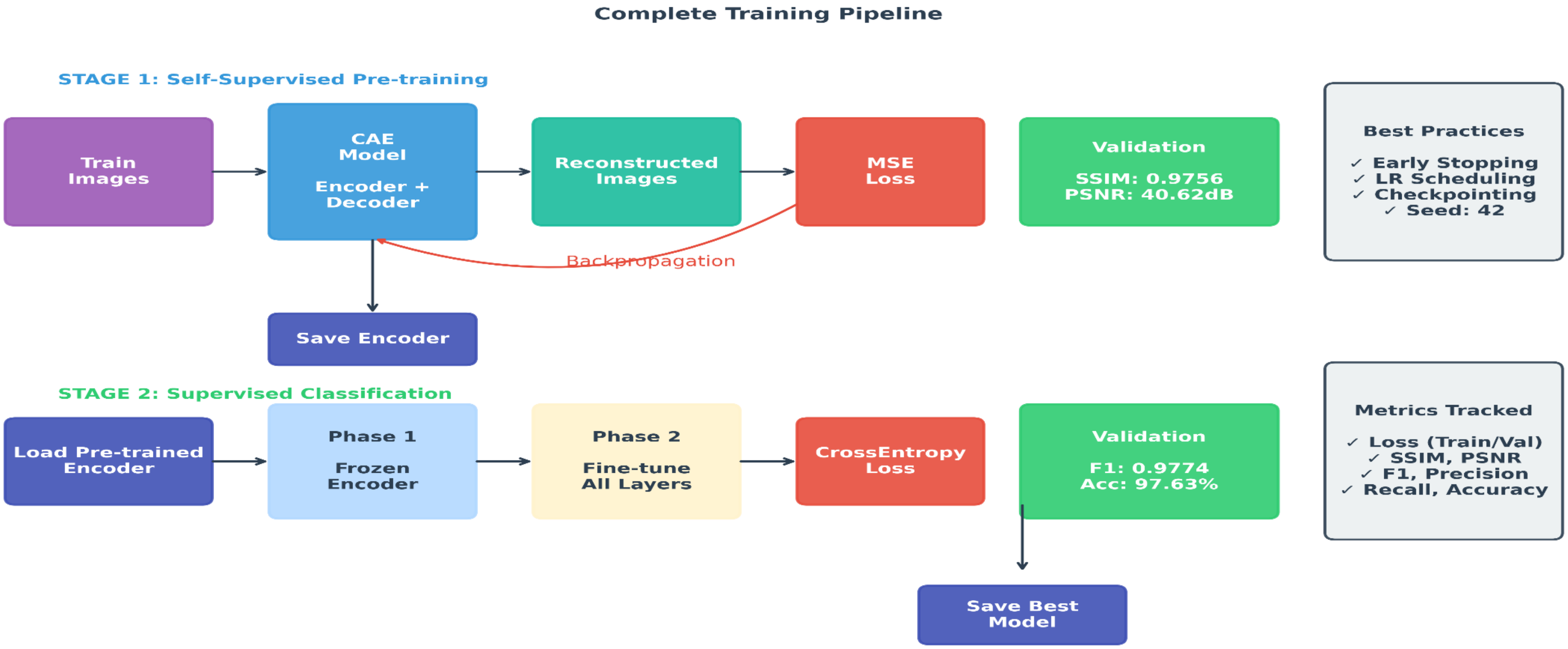


Figure 8: Training Pipeline

11. Results: CAE Reconstruction Quality

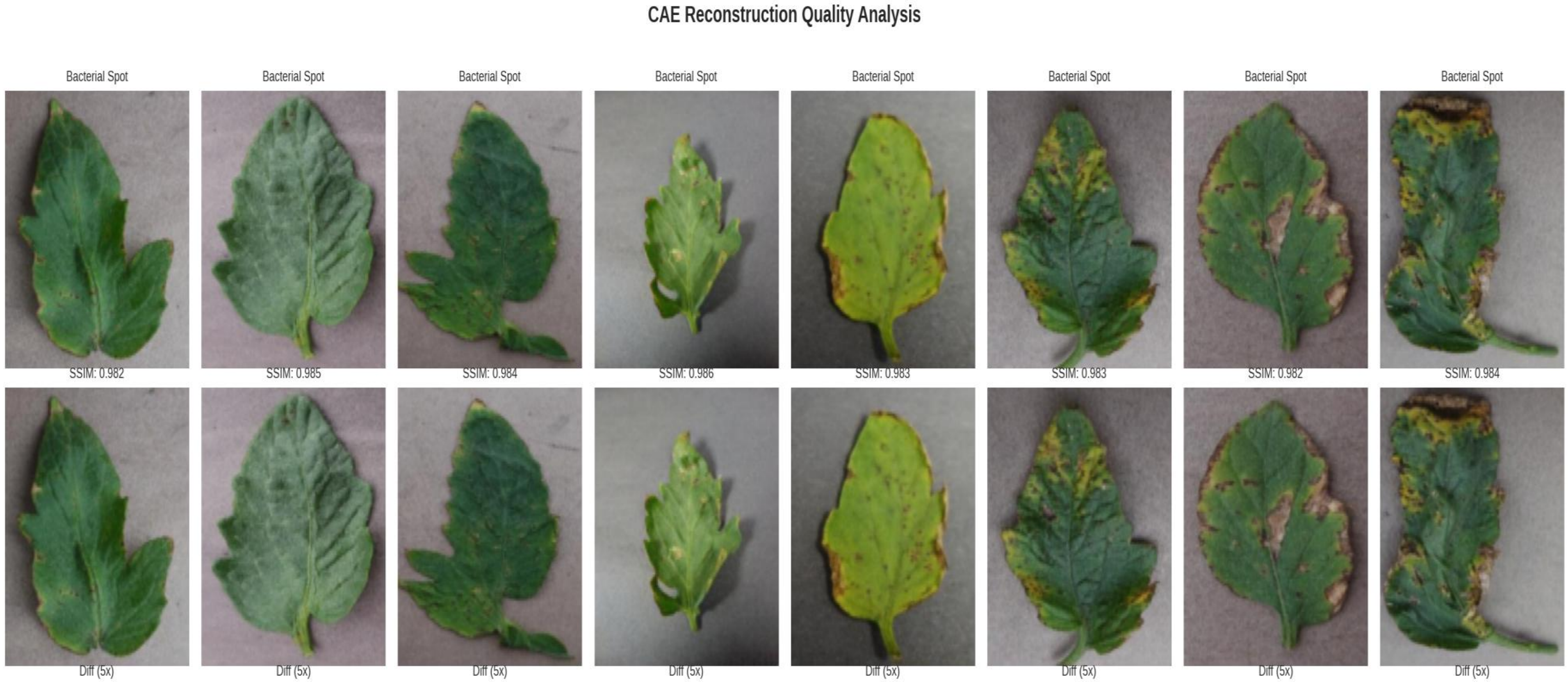


Figure 9: CAE Reconstruction

12. Results: Model Performance Dashboard

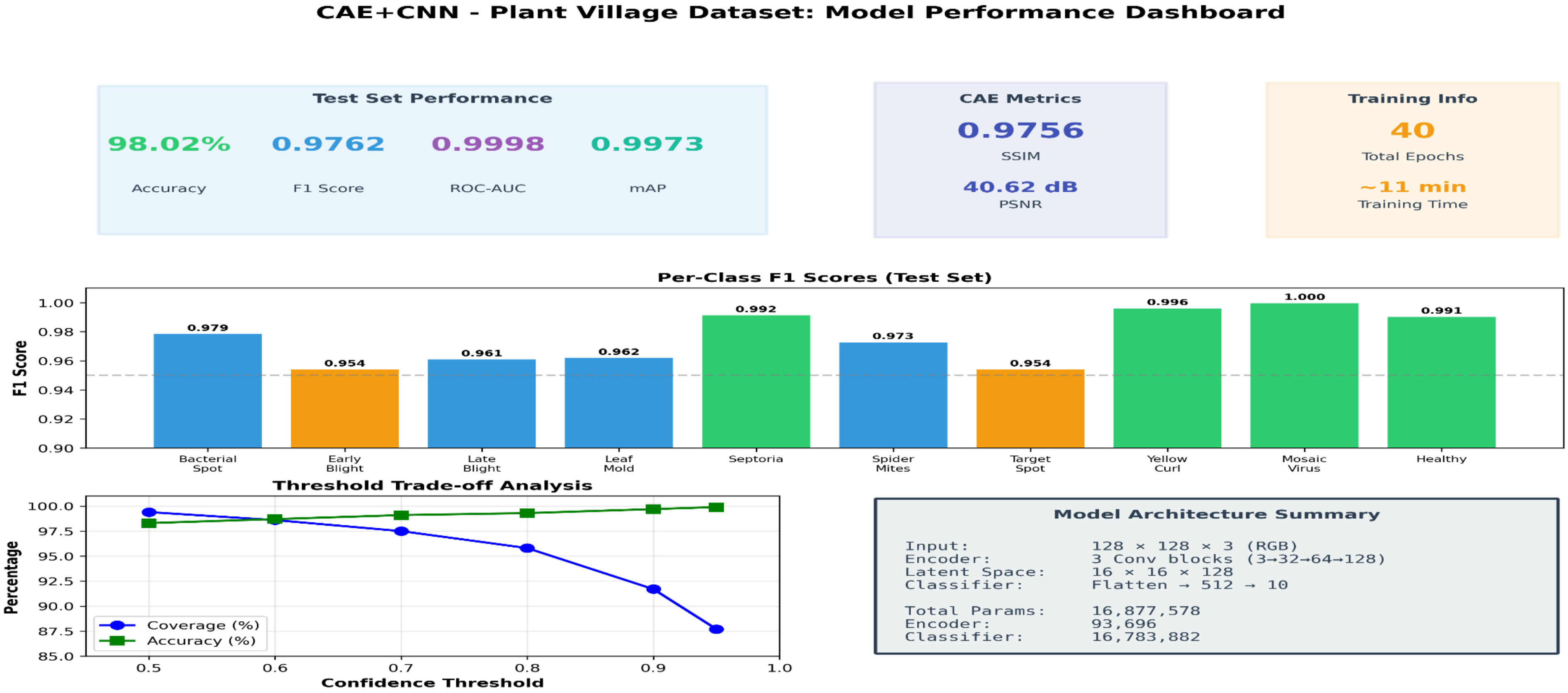


Figure 10: Performance Dashboard

13. Results: CAE Training Curves

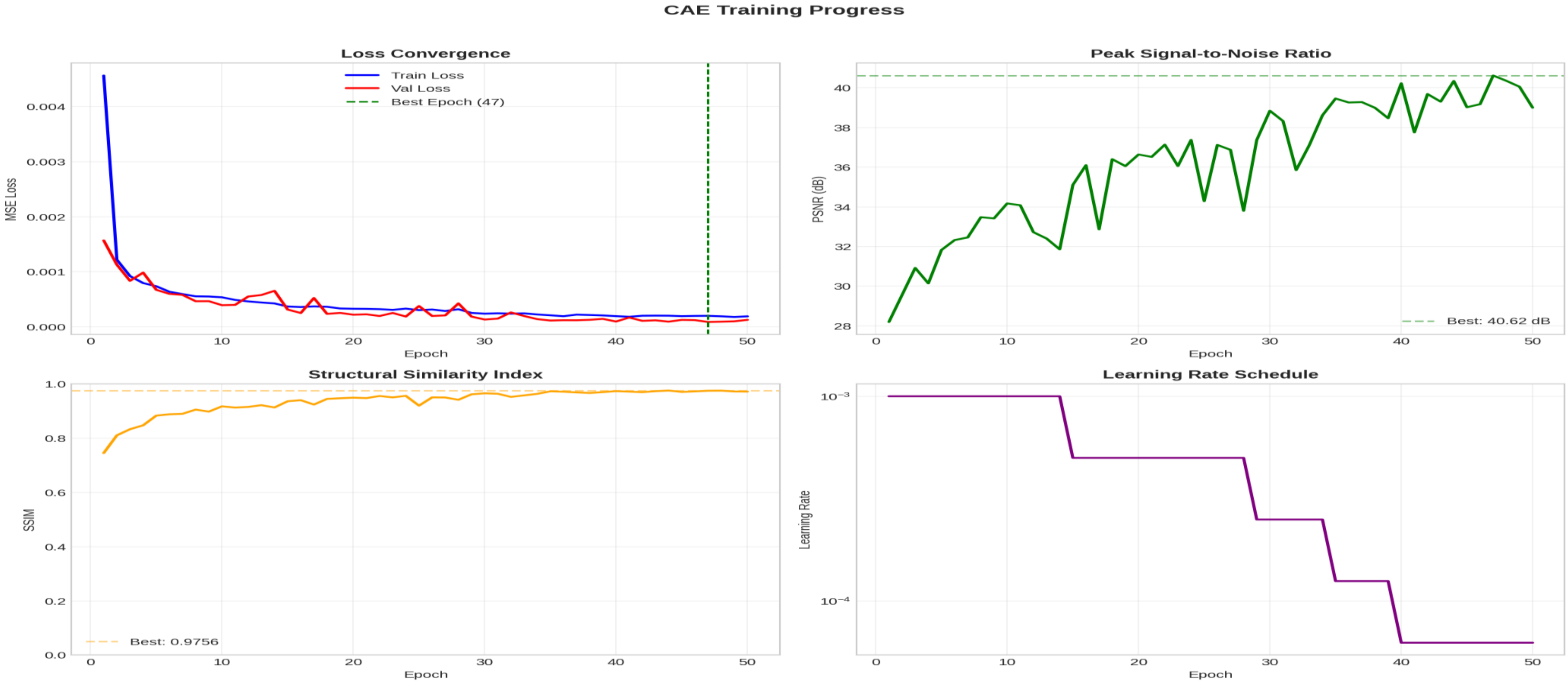


Figure 11: CAE Training Curves

14. Results: CNN Training Curves

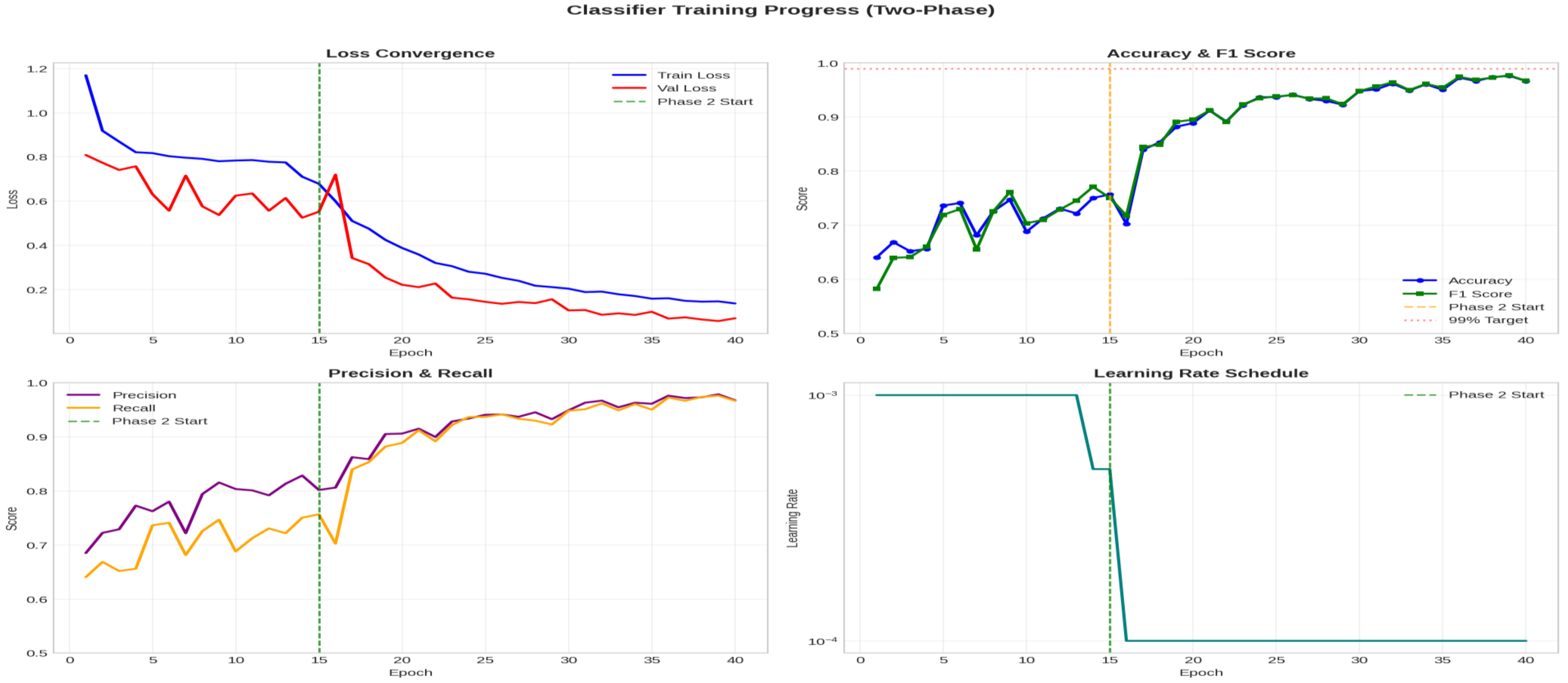


Figure 12: CNN Training Curves

15. Results: Confusion Matrix

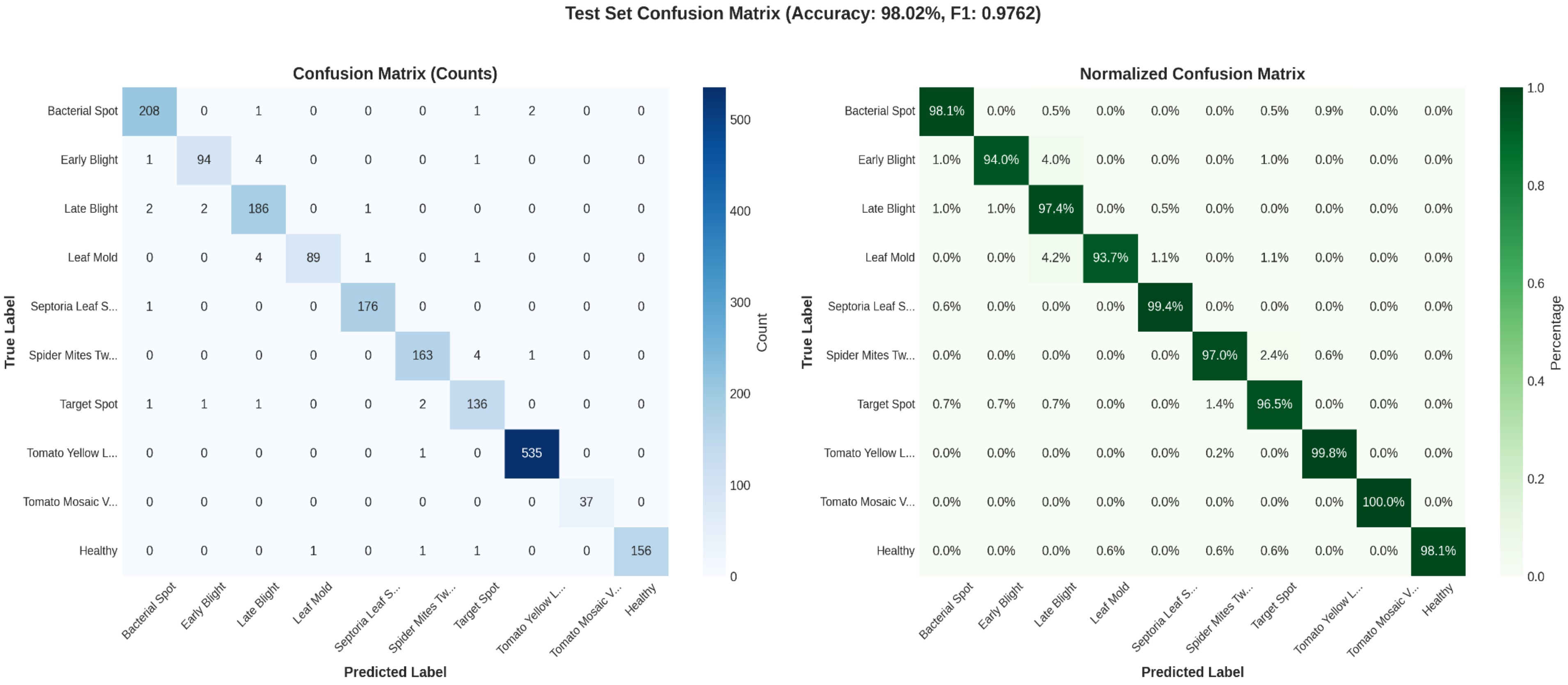
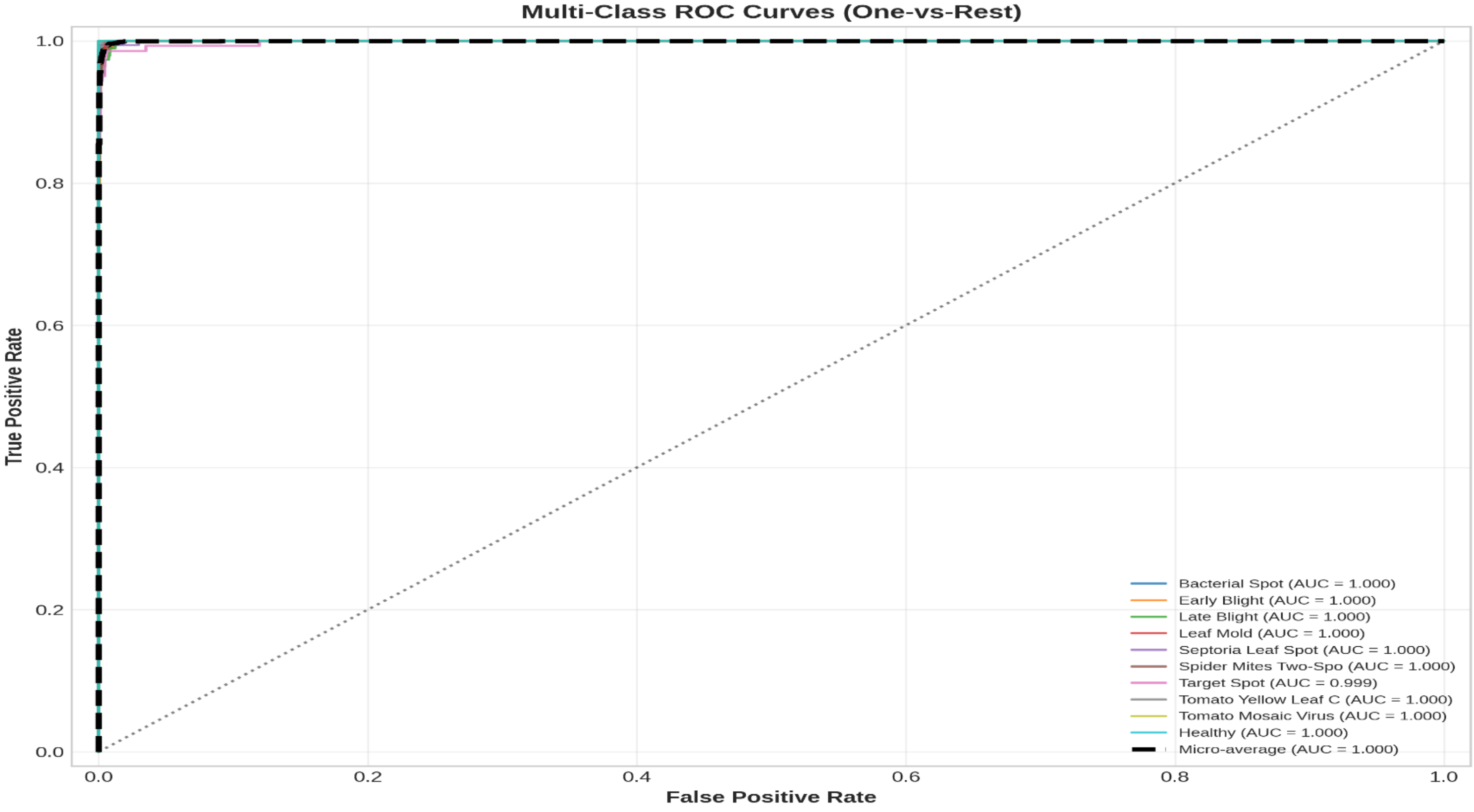


Figure 13: Confusion Matrix

16. Results: ROC Curves



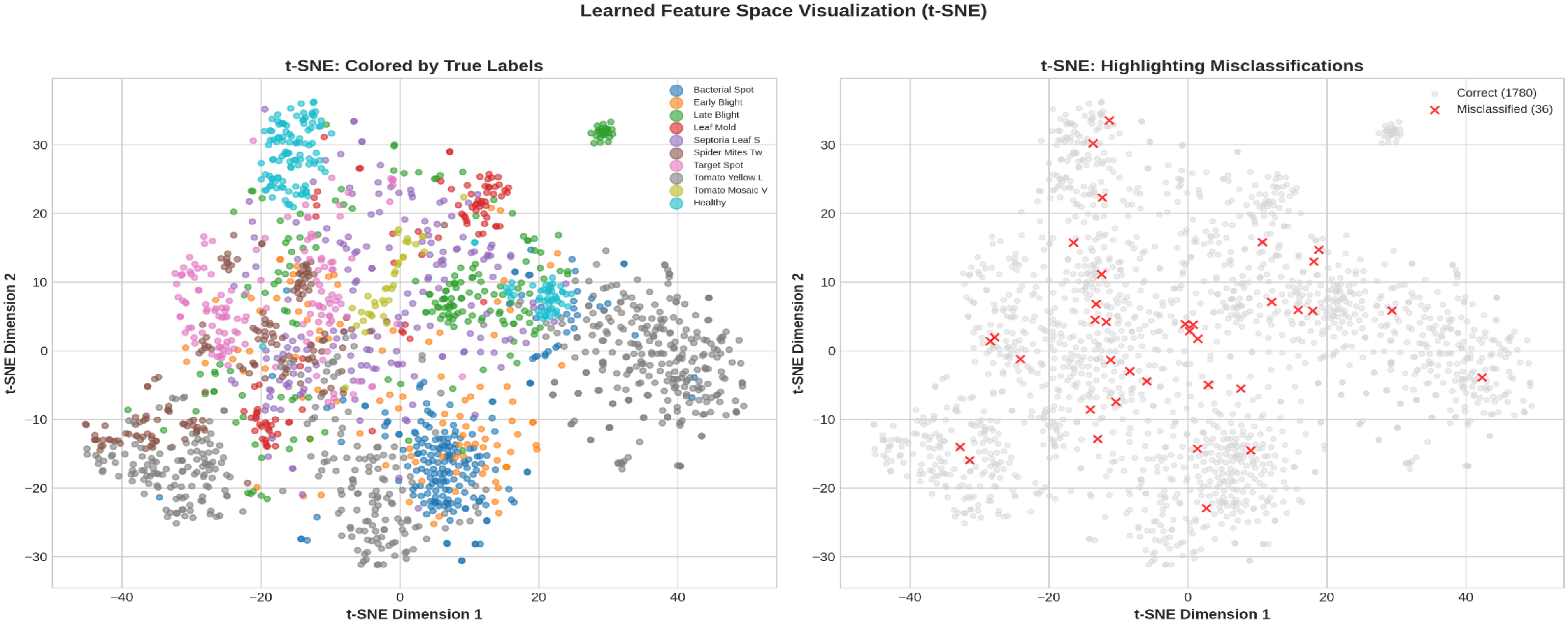
ROC-AUC: 0.9998

PR-AUC: 0.9973

mAP: 0.9973

Figure 14: Confusion Matrix

17. Feature Space Visualization



Key Finding: Clear cluster separation demonstrates effective feature extraction

Figure 15: Feature Space

18. Results: Sample Prediction (Test Dataset)

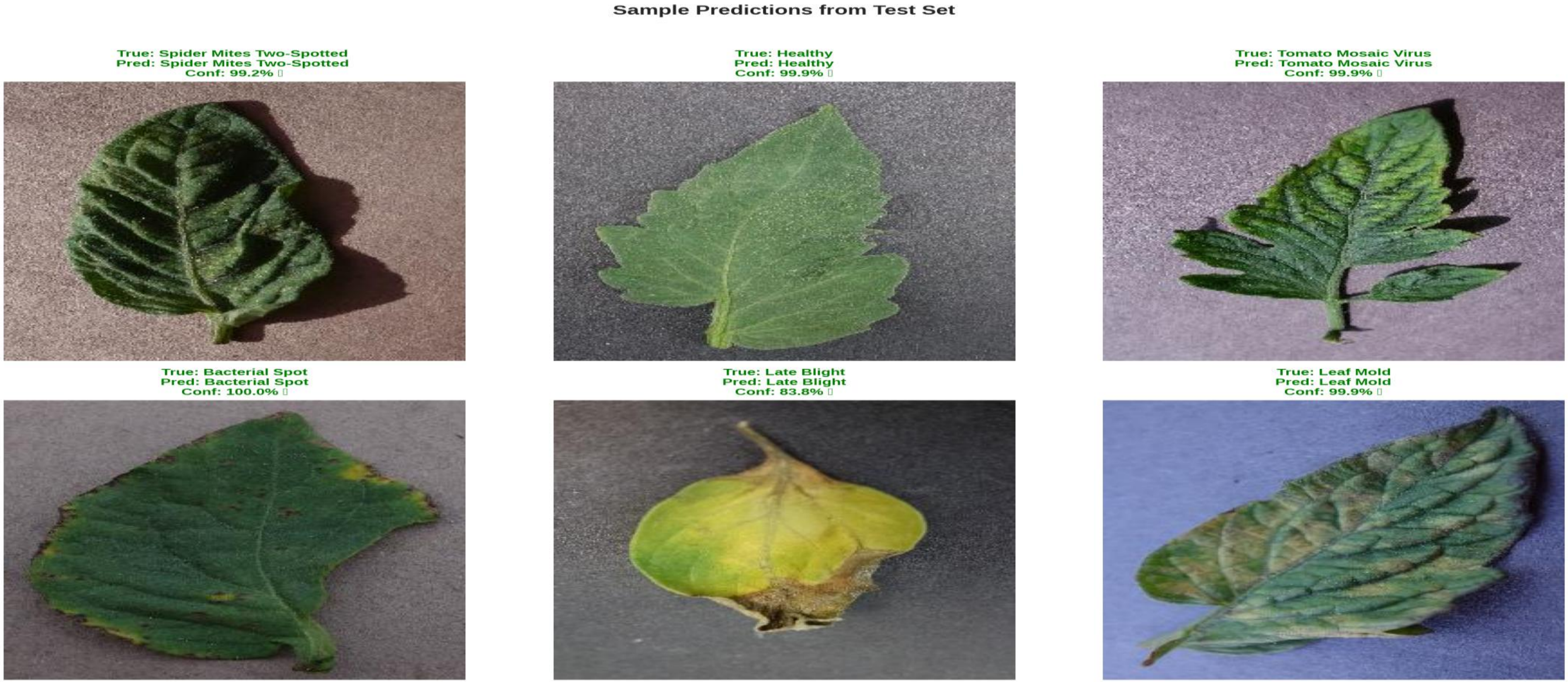


Figure 16: Sample Prediction

19. Key Results Summary

98.02%	Accuracy
0.9998	ROC-AUC
0.9787	Precision
0.9740	Recall
0.9762	F1 Score
26.7%	F1 - Improvement

Key Insights:

- Self-supervised CAE matches ImageNet transfer learning
- Two-phase training yields optimal adaptation
- All 10 classes achieve F1 > 0.95
- Lightweight (16.9M params) for edge deployment

20. Comparison with State-of-the-Art

Method	Year	Pre-training	Accuracy	F1
CNN-Stacking (Abbas)	2024	ImageNet	98.27%	0.985
T-Net (Batool)	2024	ImageNet	98.97%	-
ResNet50+MobileNet	2025	ImageNet	99.65%	-
ViT-Base	2025	ImageNet	99.17%	-
Proposed CAE-CNN	**2026**	**Self-supervised**	**98.02%**	**0.976**

Key Advantage: ONLY method achieving competitive performance (98.02%) WITHOUT ImageNet pre-training

21. Conclusion

Achievements

✓ Near-perfect discrimination (ROC-AUC 0.9998)

✓ 98.02% accuracy without ImageNet

✓ Domain-specific self-supervised learning

✓ Lightweight model (16.9M params)

Future Work

→ Mobile deployment for field use

→ Multi-crop disease detection

→ Real-field image validation

→ Severity estimation

"Self-supervised learning on domain-specific agricultural data achieves competitive performance with ImageNet transfer learning - demonstrating specialized pre-training may be more effective than generic features for plant disease detection."

Thank You

Questions?

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