PROJECT PROPOSAL

AI-Driven Diagnostic Framework for Multi-Class Tomato Leaf Pathologies:

A Dual-Stage Self-Supervised CAE-CNN Approach

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1. Introduction

Agriculture is the backbone of global food security, with tomatoes being one of the most widely cultivated and consumed crops worldwide. However, tomato plants are highly susceptible to various diseases caused by bacteria, fungi, and viruses, leading to significant yield losses estimated at 20-40% annually. Early and accurate detection of these diseases is crucial for implementing timely interventions and minimizing economic losses.

Traditional disease diagnosis relies heavily on visual inspection by agricultural experts, which is time-consuming, subjective, and often inaccessible to small-scale farmers in remote areas. The advent of deep learning and computer vision technologies offers a promising solution for automated, rapid, and accurate plant disease detection.

This project proposes DeepSpec-Tomato, a novel dual-stage deep learning framework that combines Convolutional Autoencoders (CAE) for self-supervised feature learning with Convolutional Neural Networks (CNN) for supervised disease classification. Unlike conventional approaches that rely on pre-trained models from unrelated domains, our framework learns domain-specific features directly from tomato leaf images, potentially leading to more robust and interpretable representations.

2. Problem Statement

The agricultural sector faces several critical challenges in plant disease management:

- Delayed Diagnosis: Manual inspection requires trained personnel and is often too slow to prevent disease spread, especially during peak infection seasons.
- Limited Expert Availability: Agricultural pathologists are scarce in rural areas where most farming occurs, leaving farmers without access to timely expert consultation.
- Misdiagnosis Risk: Visual symptoms of different diseases often overlap, leading to incorrect identification and inappropriate treatment application.
- Dependency on Pre-trained Models: Existing deep learning solutions often rely on ImageNet pre-trained weights, which may not capture agriculture-specific visual patterns effectively.
- Economic Impact: Crop losses due to undetected or misdiagnosed diseases significantly impact farmer livelihoods and food supply chains.

This project aims to address these challenges by developing an end-to-end deep learning solution trained entirely from scratch on agricultural imagery, ensuring domain-specific feature learning without reliance on external pre-trained models.

3. Objectives

Primary Objectives:

1. To design and implement a Convolutional Autoencoder (CAE) for self-supervised feature extraction from tomato leaf images without requiring class labels.
2. To develop a CNN-based classifier utilizing transfer learning from the CAE encoder for multi-class tomato disease classification.
3. To achieve classification accuracy of at least 75% on the test dataset, ensuring practical applicability.
4. To train all models from scratch without using any external pre-trained weights.

Secondary Objectives:

a) To evaluate reconstruction quality of the CAE using metrics such as SSIM and PSNR.

b) To implement a two-phase training strategy (frozen encoder followed by fine-tuning) to prevent catastrophic forgetting.

c) To perform threshold optimization for confidence-based predictions suitable for deployment scenarios.

d) To visualize learned feature representations using t-SNE for interpretability analysis.

e) To develop a production-ready inference pipeline for real-world deployment.

4. Proposed Method

The proposed DeepSpec-Tomato framework consists of four main phases:

Phase 1: Data Preparation

- Dataset: PlantVillage dataset (tomato subset with 10 disease classes)
- Preprocessing: Resize images to 128×128 pixels, normalize using training set statistics
- Data Split: Stratified 80/10/10 split for training, validation, and testing
- Augmentation: Random flips, rotations, and color jittering for training data

Phase 2: Self-Supervised Learning (CAE Training)

- Architecture: Symmetric encoder-decoder with 3 convolutional blocks each
- Encoder: Conv2D layers (3→32→64→128 channels) with BatchNorm and ReLU
- Latent Space: 16×16×128 dimensional bottleneck representation
- Training: MSE reconstruction loss, Adam optimizer, early stopping
- Evaluation: SSIM and PSNR metrics for reconstruction quality

Phase 3: Supervised Classification (CNN Training)

- Transfer Learning: Load pre-trained CAE encoder weights (self-trained, not external)
- Classifier Head: Flatten → Dense(512) → BatchNorm → ReLU → Dropout(0.4) → Dense(10)
- Two-Phase Training: Phase 1 with frozen encoder, Phase 2 with full fine-tuning
- Loss Function: Cross-entropy loss with F1 score for model selection

Phase 4: Evaluation and Deployment

- Test Set Evaluation: Accuracy, Precision, Recall, F1-Score, ROC-AUC
- Threshold Optimization: Analyze confidence thresholds for deployment
- Visualization: Confusion matrix, ROC curves, t-SNE feature plots
- Inference Pipeline: Production-ready prediction system with batch processing

5. Expected Outcome

Upon successful completion of this project, the following outcomes are anticipated:

Technical Deliverables:

- A trained Convolutional Autoencoder capable of high-quality image reconstruction (expected SSIM > 0.90)
- A CNN classifier achieving minimum 75% accuracy on 10-class tomato disease classification
- Complete codebase with documented Jupyter notebooks for reproducibility
- Production-ready inference pipeline for real-world deployment

Scientific Contributions:

- Demonstration of self-supervised learning effectiveness for agricultural image analysis
- Empirical comparison of frozen vs. fine-tuned encoder performance
- Interpretable feature visualization through t-SNE analysis

Practical Impact:

- Accessible disease detection tool for farmers without requiring agricultural expertise
- Potential reduction in crop losses through early disease identification
- Contribution to sustainable agriculture aligned with UN SDG 2 (Zero Hunger)

6. Project Timeline (2 Weeks)

The project will be executed over a 2-week period with the following task allocation:

Day	Task Description	Hours	Deliverable
1-2	Dataset acquisition, exploration, and EDA	8	Notebook 1
3-4	Data preprocessing, stratified splitting, normalization	6	Notebook 2
5-6	CAE architecture design and implementation	8	CAE Model
7	CAE training and reconstruction evaluation	6	Notebook 3
8-9	CNN classifier design and two-phase training	10	Notebook 4
10-11	Threshold optimization and final evaluation	8	Notebook 5
12-13	Inference pipeline and deployment preparation	6	Inference Code
14	Documentation, GitHub upload, and final review	8	Final Submission
	TOTAL	**60 hrs**	

7. Resources Required

Software Requirements:

Category	Software	Version/Purpose
Programming Language	Python	3.10+
Deep Learning Framework	PyTorch	2.0+ with CUDA support
Image Processing	torchvision, Pillow	Image transforms and loading
Data Analysis	NumPy, Pandas	Data manipulation
Visualization	Matplotlib, Seaborn	Plots and figures
ML Metrics	scikit-learn	Evaluation metrics, t-SNE

Development Environment	Jupyter Notebook	Interactive development
Version Control	Git, GitHub	Code repository

Hardware Requirements:

Component	Minimum	Recommended
GPU	NVIDIA GTX 1060 (6GB)	NVIDIA RTX 3060+ (8GB+)
RAM	8 GB	12 GB+
Storage	10 GB free space	SSD with 20 GB+
CUDA Version	11.0+	12.0+

Dataset:

- PlantVillage Dataset (publicly available)
- Tomato subset: ~18,000 images across 10 classes
- Source: Kaggle / GitHub (open access)

8. Conclusion

This proposal presents DeepSpec-Tomato, a novel dual-stage deep learning framework for automated tomato leaf disease classification. By combining self-supervised feature learning through Convolutional Autoencoders with supervised CNN classification, the proposed approach aims to develop a robust and interpretable diagnostic system without relying on external pre-trained models.

The project addresses critical challenges in agricultural disease management by providing an automated, accessible, and accurate diagnostic tool. With a target accuracy exceeding 75%, the system has the potential to significantly impact sustainable farming practices and food security initiatives aligned with UN Sustainable Development Goals.

The 2-week implementation timeline, supported by adequate computational resources and a well-defined methodology, ensures feasibility and timely completion. Upon successful execution, this project will contribute both technically through novel self-supervised learning applications in agriculture, and practically by enabling farmers to identify crop diseases early and implement appropriate interventions.