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FACULTY OF ENGINEERING

AI-Based Image Processing Module for Plant Disease Detection In the Uyumsoft ZiraiTakip Application

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IE 4197 ENGINEERING PROJECT
FINAL REPORT

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We also extend our thanks to the academic staff of the Marmara University Industrial Engineering Department for providing a stimulating learning environment and the necessary resources to complete this research.

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ABSTRACT

Key Words: Agriculture 4.0, Vision Transformers, Class-Incremental Learning, LoRA, Edge Computing, Plant Disease Diagnosis.

Turkey's economy heavily relies on the agricultural sector; thus, the adoption of digital precision management in agriculture has to be done in order to maintain food security and global competitiveness. Nevertheless, the implementation of AI models at the end of mobile networks has to go through two significant issues: the first issue is "catastrophic forgetting," which is a situation when the model is trained on new diseases and it forgets the previous knowledge, and the second issue is the limitations of mobile hardware.

To overcome these difficulties, the suggested project proposes an adaptive vision architecture that rejects the use of the traditional object detection models like YOLOv8n, which require a lot of computation. Instead, it suggests a classification model based on the DINOv2 Vision Transformer (ViT) with Low-Rank Adaptation (LoRA) for better performance. The initial findings reveal that while YOLOv8n undergoes 100 training cycles to get to 92.xx% accuracy, the proposed method gives much higher 97.88% accuracy in only 10 cycles, and this is a 10-fold rise in learning efficiency. Besides, the use of LoRA cuts down trainable parameters to only 2%, which makes the updates on edge devices memory-efficient.

This paper reports the accomplishment of the first part of the project and the truth of the architectural structure. In the next step, the focus will be on the integration into the Uyumsoft ZiraiTakip mobile ecosystem in real-time and carrying out wide-ranging field tests. The results of the study give a credible route for the "lifelong learning" machines in agriculture that adapt to new biological hazards while keeping the existing knowledge intact.

ABBREVIATIONS

ANN: Artificial Neural Network

CNN: Convolutional Neural Network

ViT: Vision Transformers

PEFT: Parameter-Efficient-Fine-Tuning

LoRA: Low-Rank Adaptation

NLP: Nature Language Processing

RT-DETR: Real Time Detection Transformer

SSL: Self-Supervised Learning

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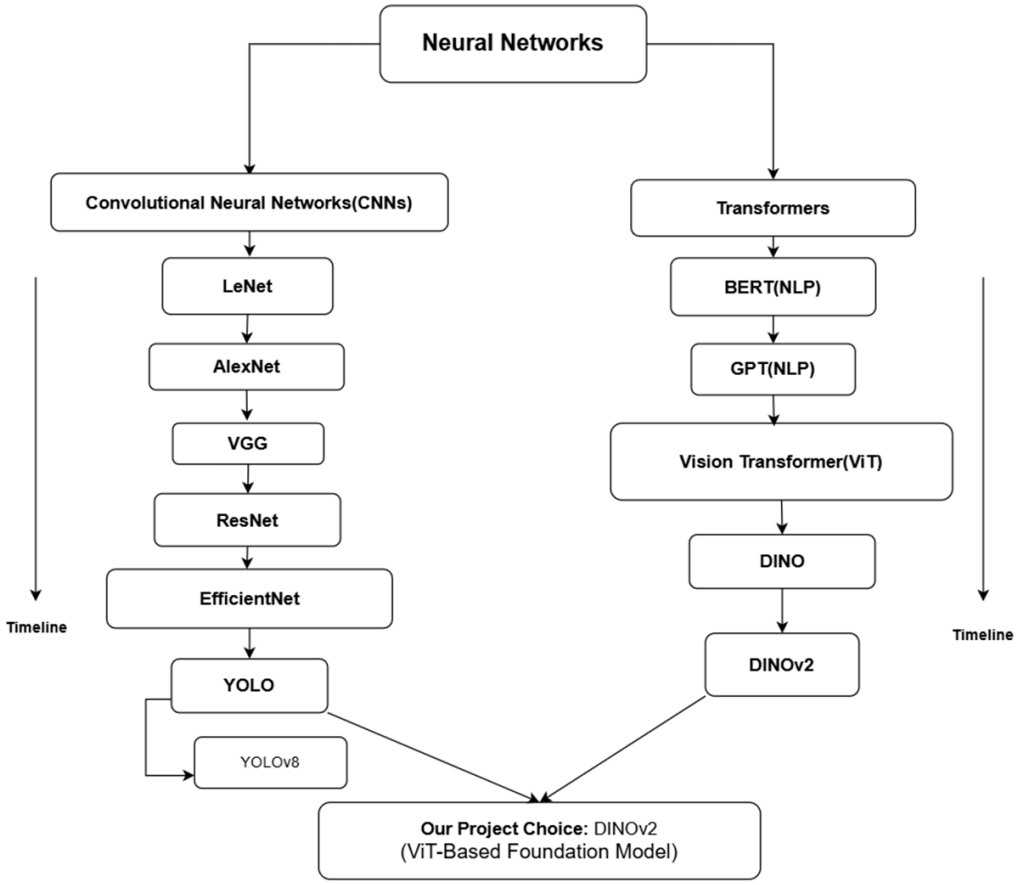

Figure 1 Evolution of Deep Learning Architectures: CNNs and Transformers

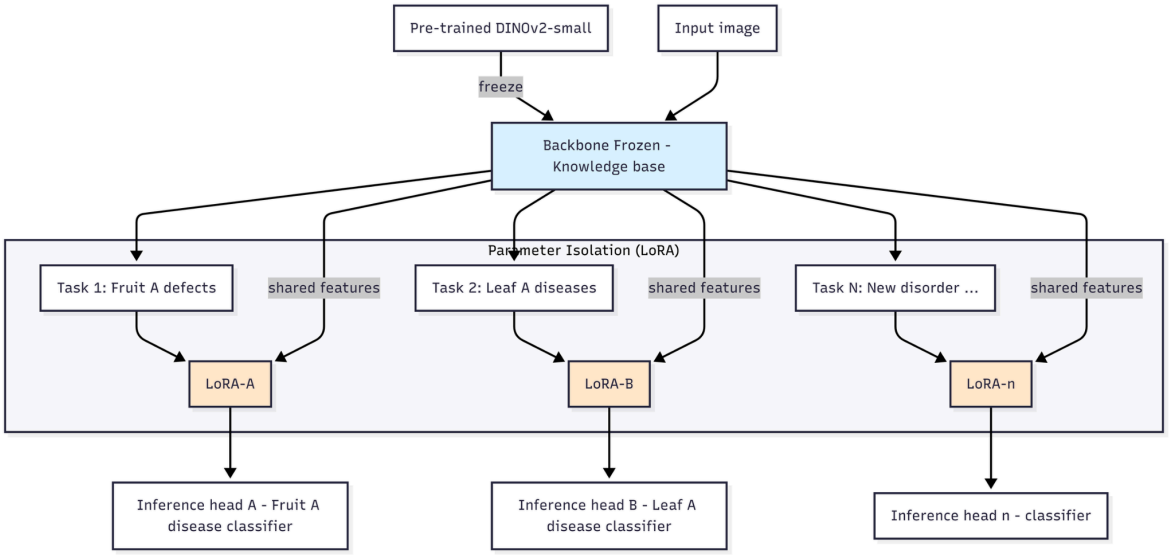

Figure 2 System Design

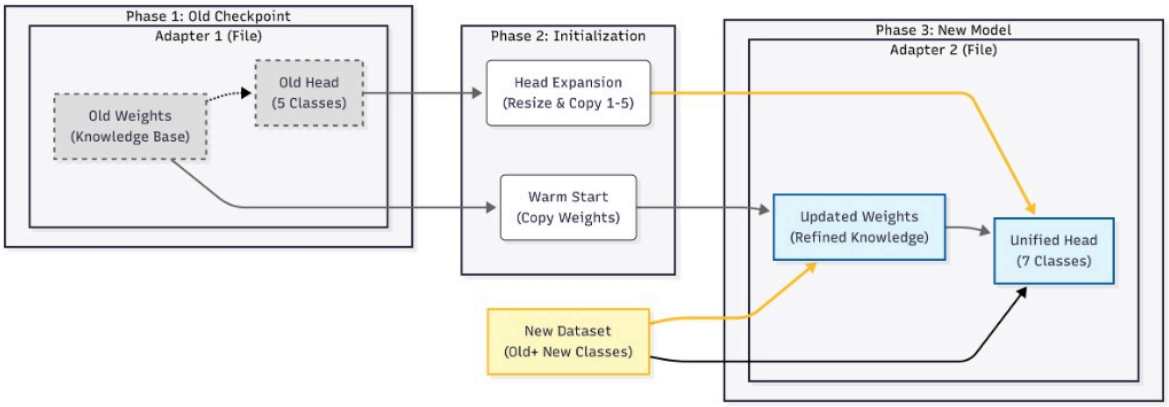

Figure 3 Continual Learning

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Articles	Methods	Key Takeaways for Our Project
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Resource Efficiency(Aggarwal et al., 2024)	Proves PEFT maintains high accuracy with low compute power.	Validates that we don't need a cloud GPU; works in resource-constrained fields.
Generalization(Espejo-Garcia et al., 2025)	DINOv2 + LoRA learns structure better than CNNs.	Prevents over-fitting (memorization) by learning the plant geometry, not just pixels.
Mobile Deployment,(Xu et al., 2023 - QA-LoRA)	Quantization + LoRA: Combines adapter efficiency with INT8 compression.	Enables running heavy models on drones/mobile edge devices without latency.

Table 1 Literature Table of LoRA

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National: Endemic Varieties(Aegean & Black Sea Research)	Collecting data for every local variety (Olive/Hazelnut) in complex topography is unfeasible.(Data scarcity)	**Few-Shot Learning**: We implement a Frozen Backbone strategy that learns new endemic classes with only 4-16 examples.
National: Turkish Agriculture(Kahya & Aslan, 2024)(Kahya et al., 2024)	Local studies focus on single-crop (e.g., olive,tea,watermelon) solutions with standard YOLO.	Bridging the Scalability Gap: Identified the **lack of Continual Learning**; proposed a dynamic system for multi-crop adaptation.

Table 2 Table of Literature Review

Disease Class	Precision	Recall	F1-Score
Bacterial Spot	0.960	0.957	**0.958**
Early Blight	0.984	0.955	**0.969**
Late Blight	0.963	0.987	**0.975**

Leaf Mold	0.965	0.974	**0.970**
Septoria Leaf Spot	0.942	0.945	**0.944**
Spider Mites	0.980	0.987	**0.984**
Target Spot	0.987	0.987	**0.987**
Mosaic Virus	0.991	0.995	**0.993**
Yellow Leaf Curl Virus	0.995	0.972	**0.984**
Healthy	0.987	0.997	**0.992**
OVERALL ACCURACY			**97.3%**

Table 3: Performance Metrics - Tomato Leaf Adapter (Validation Split)

Defect Class	**Precision**	**Recall**	**F1-Score**
Anthracnose	1.000	0.889	**0.941**
Blossom End Rot	0.958	0.986	**0.972**

Fruit Cracking / Gray Mold	1.000	1.000	**1.000**
Healthy Fruit	1.000	0.983	**0.992**
OVERALL ACCURACY			**98.7%**

Table 4: Performance Metrics - Tomato Fruit Adapter (Validation Split)

WORK PLAN:

Duration	Work Package (WP)	Activities	Deliveries	Responsibility
Weeks 1 – 3	**WP1: Defining the Problem**	• Definition of the "Stability-Plasticity Dilemma" in agricultural AI. • Identification of specific pathologies and the need for separate diagnostic streams.	• Project Proposal Document. • Formal Problem Statement. • Research Questions and Objectives Definition.	Doğa Şener
Weeks 4 – 7	**WP2: Literature Review & Contextual Analysis**	• Review of SOTA methods: Vision Transformers (ViT), DINOv2, and Continual Learning. • Analysis of Parameter-Efficient Fine-Tuning (PEFT) techniques, specifically LoRA. • Examination of existing agricultural datasets (PlantVillage, Kaggle) to identify gaps in 3D/volumetric defect data.	• Literature Review Chapter. • Comparative Analysis of existing unified vs. modular models.	Berke Öz
Weeks 9 – 11	**WP3: Validating Data and Identifying Tools**	• Acquisition and cleaning of raw image data. • Dividing data into isolated "Leaf" and "Fruit" directories. • Setup of the Simulation Environment (Google Colab Pro, A100 GPU). • Installation and verification of PyTorch, Hugging Face transformers, and peft libraries.	• Validated Dataset (Cleaned, Resized to 224 x 224, Normalized). • Confirmed Software Stack & Hardware Infrastructure.	Efe Erim

Weeks 12 – 14	**WP4: Method Identification and Conceptual Modeling**	• Architectural design of the **Parameter Isolation Framework**. • Design of the independent adapter development protocol	• Methodology Chapter. • System Architecture Diagram.	Efe Erim

1. INTRODUCTION

Problem Definition

The Strategic Imperative: Agriculture 4.0 in Turkey

Turkey is a leading country in both global and regional agricultural production and the main supplier for Europe and the Middle East. But to keep this advantage and ensure the availability of food for a long time, it is necessary to transform "Agriculture 4.0" completely. The agricultural sector will be digitized not as an option but a systemic necessity to be able to compete globally and produce high-quality food. The transition to proactive, data-driven precision management is absolute for the survival of Turkey's large agricultural area.

The Diagnostic Gap and Economic Loss

One of the major problems that Turkish farmers encounter is that they cannot have access to quick, accurate, and expert-level diagnosis of plant diseases. Most of the times, the disease is manually diagnosed, which is a labor-intensive, reactive, and error-prone process. Often, the pathogen identification is quite late as the infection has already spread widely. The farmers would be armed with the necessary tools to start and carry on focused treatments right after the disease appeared, which would tremendously benefit the farmers resulting in significant savings in both operational time and input costs.

The Technical Crisis: Rigidity and Resource Constraints

In addition to the operational problems, there is a huge technical problem hindering the Artificial Intelligence in precision agriculture deployment:

The Stability-Plasticity Paradox: Biological ecosystems are dynamic and non-stationary, with new pathogen strains and environmental conditions emerging seasonally. Current neural networks used in agriculture often suffer from "Catastrophic Forgetting"; when updated to learn a new disease, they erase previously acquired knowledge, making them obsolete for long-term field use.

The Mobile/Edge Computational Barrier: High-fidelity diagnostic models like Vision Transformers (ViTs) are computationally intensive. Deploying these models on the "edge"

where farmers operate using mobile devices or autonomous robots—is restricted by the limited memory, battery, and processing power of hardware such as the NVIDIA Jetson platform.

Methodological Inefficiency: Many existing systems focus on "Object Detection" (e.g., YOLO), which prioritizes finding the location of a leaf rather than conducting a deep semantic analysis of its health. This results in wasted computational effort on defining external contours when the actual need is a deep analysis of internal morphological signatures to identify specific pathologies.

Project Objective

In order to tackle these complex issues from different angles, this project proposes an adaptive vision architecture based on DINOv2 and LoRA. The objective of this methodology is to merge the efficiency of mobile edge deployment with the precision of state-of-the-art Vision Transformers and to allow for gradual learning that continuously adapts to the farm's biological reality.

2. RESEARCH OBJECTIVE

Artificial Neural Networks (ANNs) are computational systems composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These systems learn to map inputs to outputs by adjusting the weighted connections between neurons through backpropagation, enabling them to solve complex tasks such as image recognition and natural language processing. (LeCun et al., 2015).

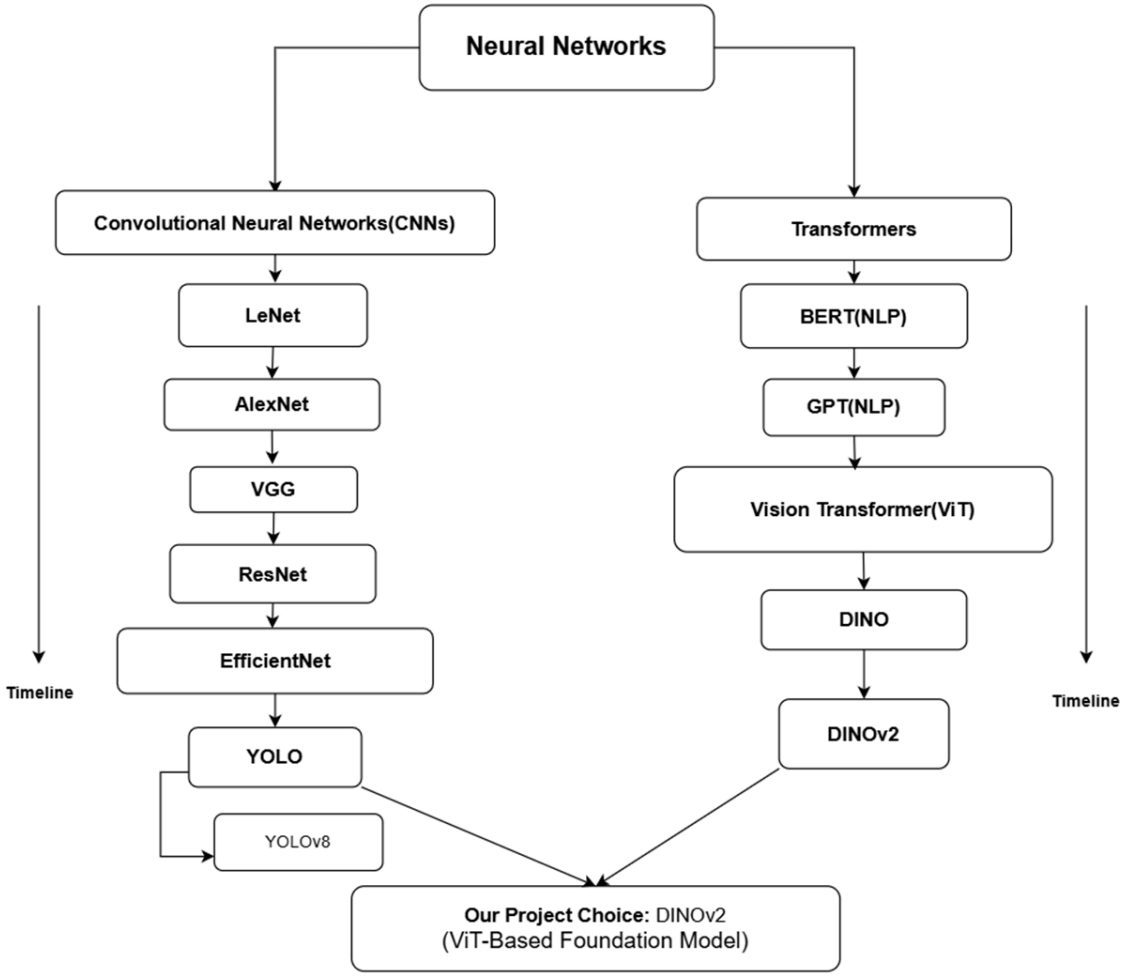

Figure 1 Evolution of Deep Learning Architectures: CNNs and Transformers

Visual computing technologies have become a critical lever in reaching productivity,sustainability, and food security goals in the agricultural sector. Precision agriculture applications, which have replaced traditional methods, rely heavily on deep learning models for the early diagnosis of plant diseases, weed control, yield estimation,

and robotic harvesting. In this context, the DINOv2 architecture introduced by Meta AI has set a new standard in computer vision with its Vision Transformer (ViT)-based structure and Self-Supervised Learning (SSL) paradigm. (Oquab et al., 2023).

In a geography like Turkey, where biodiversity is high and agricultural production is a cornerstone of economic development, DINOv2's "out-of-the-box" high-performance feature extraction capabilities constitute a powerful alternative to traditional supervised learning methods and the popular YOLO (You Only Look Once) series models. (Bai et al., 2024).

Why did we choose DINOv2 instead of YOLO?

YOLO is based on Convolutional Neural Networks (CNNs). CNNs learn local features by scanning the image with sliding windows, which inherently limits the model's receptive field to a specific area of the image at any given time. In contrast, DINOv2, being based on the Vision Transformer (ViT) architecture, utilizes a self-attention mechanism that calculates the relationship of each pixel with all other pixels in the image simultaneously (Oquab et al., 2023). In the context of agriculture, this capability is critical; it allows the model to analyze the entire plant structure and its surroundings to understand its general health and distinguish complex disease patterns, rather than relying solely on the local texture of a single leaf (Reedha et al., 2022; Bai et al., 2024).

DINOv2 was trained on a curated dataset of 142 million images (LVD-142M) and learned object parts, textures, and semantic boundaries without human intervention.(Oquab et al., 2023). Literature shows that DINOv2's "frozen" features possess better discriminative power than a fully trained YOLO model.(Oquab et al., 2023).

DINOv2's global attention mechanism (Self-Attention) captures complex and scattered patterns of plant diseases (e.g., mosaic virus) much more effectively than YOLO's local convolutions. This method will demonstrate that this transition is not just a preference, but an engineering necessity for the project to reach its "mobile, extensible, and high-accuracy" goals.(Dosovitskiy et al., 2020; Oquab et al., 2023)

Statement of the Problem and Need for the Study

Turkey is a critical center and one of the world leaders in agricultural sector within Europe and the Middle East, particularly in the cultivation of olives, hazelnuts, tomatoes, and

cereals. To ensure the sustainability of this production capacity, maintain global competitiveness, and guarantee food quality, digital agricultural transformation is no longer an option, but a necessity.

Despite this potential, farmers face significant challenges in accessing accurate and rapid diagnoses of plant diseases. In traditional methods, misdiagnosis or delayed intervention often leads to incorrect pesticide use and substantial yield loss. Enabling farmers to begin the correct treatment quickly via early diagnosis will make a positive difference in the agricultural sector in terms of saving both time and production costs.

However, current digital solutions in the local market are insufficient to meet this need. Local academic studies have predominantly focused on single-crop models (e.g., specifically for olives or watermelons), creating a scalability gap for Turkey's rich biodiversity. Therefore, there is an urgent need for a unified multi-crop disease detection system. In this context, the proposed DINOv2 architecture provides innovative solutions for the varying light conditions and plant variations encountered in Turkey's agricultural ecosystem.

Sub-problems of Our Project

While Foundation Models like DINOv2 offer superior feature extraction capabilities compared to traditional CNNs, adapting them to the resource-constrained agricultural field introduces specific sub-problems that this project aims to solve.

Computational Cost and Resource Efficiency (Hardware Constraints): Large-scale models contain millions of parameters, making them computationally intensive to fine-tune or deploy on the standard mobile devices used by farmers. As highlighted by Aggarwal et al. (2024), there is a critical need to prove that high accuracy can be maintained with low compute power to validate operation in resource-constrained fields without relying on cloud GPUs. Additionally, enabling these heavy models to run on drones or mobile edge devices without latency requires specific optimization techniques, such as quantization-aware adaptation, as proposed by Xu et al. (2023).

Catastrophic Forgetting (Continual Learning): In a multi-crop scenario, traditional fine-tuning methods often cause the model to "forget" previously learned diseases when trained on a new plant type. The system requires a "Continual Learning" capability to

adapt to new endemic varieties without retraining from scratch.(Liu et al.,2023) emphasize the importance of using task-specific adapters while freezing the main model backbone to retain knowledge of old diseases while learning new ones.

This project utilizes **Parameter Efficient Fine-Tuning (PEFT)**. PEFT is a methodology to adapt large pre-trained models to specific tasks by updating only a small fraction of parameters. LoRA (Low-Rank Adaptation) is a Parameter-Efficient Fine-Tuning (PEFT) method that adapts massive AI models to new tasks by training only a tiny subset of parameters (adapters) rather than the entire model.

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Table 1 Literature Table of LoRA

By integrating LoRA with DINOv2, the project aims to build a robust domain adaptation system specific to the diverse agricultural landscape in Turkey while minimizing hardware costs.

3. RELATED LITERATURE

Articles from the World

Globally, researchers have successfully developed multi-crop disease detection models utilizing large public datasets like PlantVillage. For instance, Mohanty et al. (2016) achieved high accuracy across 14 different crop species using traditional CNN architectures such as AlexNet and GoogLeNet. Similarly, Too et al. (2019) demonstrated that DenseNet architectures could classify 38 different disease classes across multiple plants. However, these studies mostly rely on Supervised Learning with fixed classes (Closed-Set) and lack the 'Continual Learning' capability. If a new crop needs to be added, these traditional models require retraining from scratch with thousands of images.

To address the limitations of traditional CNNs and handle complex environmental challenges, the field is undergoing a paradigm shift to Vision Transformers (ViT). A critical weakness of CNNs is their heavy reliance on texture, which leads to failure in "Green-on-Green" scenarios where weeds and crops share similar spectral characteristics. Addressing this, Reedha et al. (2022) demonstrated the superiority of ViTs in soybean crops, revealing that they leverage shape-oriented attention mechanisms to distinguish weeds without extensive labeling. Furthermore, occlusion—where fruits are hidden by leaves—remains a persistent challenge. Lv et al. (2023) addressed this with the RT-DETR model, proving that Transformer-based architectures excel in inferring the complete shape of partially visible objects by utilizing global context, thereby outperforming traditional YOLO models in complex harvesting environments.

Articles from Turkey

In Turkey, agricultural digitalization is driven by both strategic state initiatives and academic research.

- **State Initiatives:** The **AKTAR (Smart Agriculture Feasibility)** project, conducted by **TÜBİTAK UZAY**, utilizes drone and satellite imagery to monitor strategic crops like wheat and sugar beets in Central Anatolia. Similarly, **GAPHASSAS**, developed by the **GAP Regional Development Administration**, aims to disseminate precision agriculture across the GAP region. However, monitoring these vast, heterogeneous regions with traditional supervised learning

requires massive, region-specific labeled datasets, creating a significant labeling bottleneck.

- **Local Academic Studies:** Prominent works by **Kahya and Aslan (2024)** and **Kahya et al. (2024)** have successfully applied Deep Learning for olive and watermelon disease detection. While effective, these studies rely on standard YOLO architectures trained on single-crop datasets. This approach remains static; the models lack the "Continual Learning" capability required to adapt to Turkey's rich endemic biodiversity (e.g., Aegean olives, Black Sea hazelnuts) without retraining from scratch.

The Contribution of Our Study

A critical review of the literature identifies a **"Scalability Gap"** in Turkey. Current local solutions are effective for specific crops but fail to scale across the country's diverse agricultural landscape due to high data requirements and hardware limitations. This project aims to solve these gaps through three key contributions:

1. **Continual Learning:** To prevent "Catastrophic Forgetting" when adapting to new crops, this study utilizes a Frozen Backbone strategy with task-specific adapters, as suggested by Liu et al. (2023). This allows the model to retain knowledge of previous diseases while learning new ones.
2. **Resource Efficiency:** Validating the findings of Aggarwal et al. (2024), this project demonstrates that high accuracy can be maintained with low compute power using Parameter-Efficient Fine-Tuning (PEFT), eliminating the need for expensive cloud GPUs.
3. **Mobile Deployment:** Addressing the hardware constraints of Turkish farmers, the study employs QA-LoRA (Quantization-Aware LoRA). As proposed by Xu et al. (2023), this technique combines adapter efficiency with quantization, enabling heavy Foundation Models to run on drones and mobile edge devices with minimal latency.

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Table 2 Table of Literature Review

4. METHODOLOGY

System Design: Parameter Isolation

This study implements a **Class-Incremental Learning** system. Unlike traditional continual learning approaches that rely on regularization or replay buffers to protect old knowledge, this architecture enforces **strict physical isolation** of task parameters.

The system is composed of a fixed foundation and a dynamic library of independent modules:

1. **Shared Backbone (Frozen):** We utilize **DINOv2-small** as the universal feature extractor. Its weights (Θ_{base}) remain frozen at all times, ensuring that the fundamental visual representation (edges, textures, shapes) is never altered.
2. **Independent Expert Modules (LoRA Adapters):** Each plant domain is assigned a completely separate Low-Rank Adaptation (LoRA) module.
    - The Tomato Leaf adapter and Strawberry Fruit adapter are distinct sets of weights.
    - There is **no shared memory** or weight transfer between adapters. Adapter A is never used to initialize or train Adapter B.
3. **Targeted Update Mechanism:** When new data becomes available for a specific domain (e.g., new images of Tomato Leaf diseases), **only** the corresponding module is unlocked and updated. All other modules remain offline and strictly unaffected.

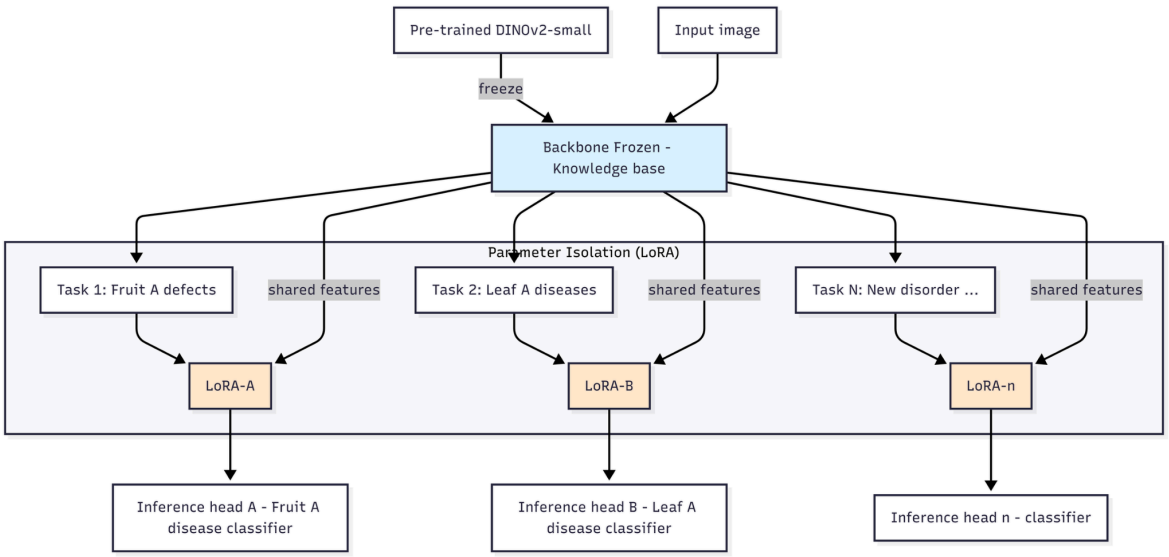

Figure 2 System Design

4.2. Algorithm: Independent Adapter Optimization

The core of this study is the shift from "Sequential Fine-Tuning" (where weights are overwritten) to **" Parameter Isolation."** The learning process treats each semantic domain (Leaf vs. Fruit) as a standalone optimization problem, sharing only the frozen backbone.

4.2.1. Mathematical Formulation

Let the pre-trained DINOv2 backbone be defined by weights Θ_{base}. We define our system not as a single model, but as a **Library of Adapters** $\phi = \{\phi_{leaf}, \phi_{fruit}\}$

For any specific domain D (e.g., Tomato Leaf), the model output y is computed as:

$$y = Head_D(DINOV2(x;\Theta_{base}) + LoRA(x;\phi_D))$$

Where:

- Θ_{base}: **Frozen.** These parameters are never updated.
- ϕ_D: **Trainable.** The domain-specific adapter weights (*A, B* matrices).
- $Head_D$: **Trainable.** The specific classification layer for that domain (e.g., 10 classes for Leaf, 4 classes for Fruit).

4.2.2. Development of LoRA Adapters

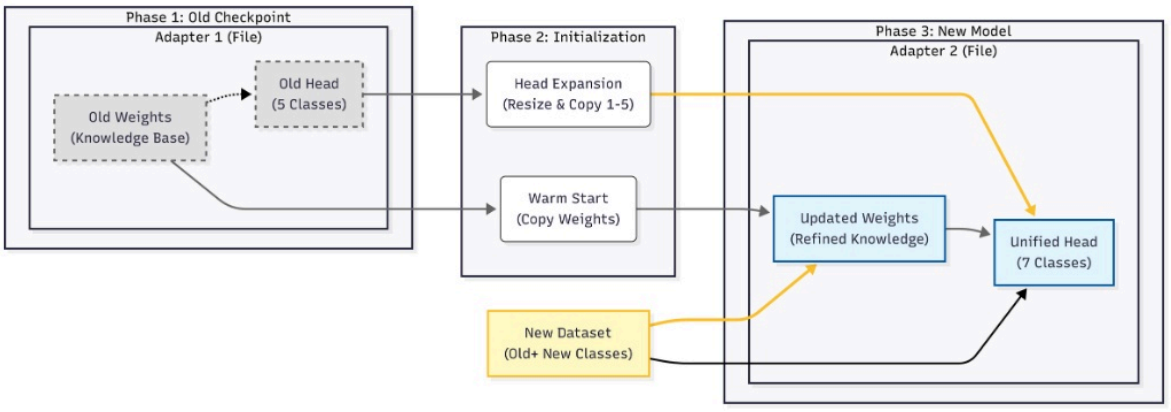

Figure 3 Continual Learning

Step 1: Independent Initialization When a new domain is introduced (e.g., Module 2: Fruit), we initialize a new adapter set ϕ_{fruit} with random Gaussian weights for Matrix A and zeros for Matrix B.

Step 2: Targeted Optimization We optimize the specific adapter parameters to minimize the Cross-Entropy Loss (L_{CE}) on the domain-specific dataset D_{fruit}

$$\min_{\phi_{fruit}, \text{Head}_{fruit}} \sum_{(x,y) \in \mathcal{D}_{fruit}} \mathcal{L}_{CE}\Big(f(x; \theta_{base}, \phi_{fruit}), y\Big)$$

During this step:

1. **Backbone (Θ_{base}):** Frozen (Requires_Grad = False).
2. **Other Adapters (ϕ_{leaf}):** Offline/Unloaded. They are mathematically non-existent during this run.

Step 3: Storage and Switching

Upon convergence, only the delta-weights (ϕ_{fruit}) and the specific head ($Head_{fruit}$) are saved.

- **Inference Logic:** At runtime, the system performs a "Hot Swap." If the input is a Leaf, ϕ_{leaf} is loaded into the backbone. If the input is a Fruit, ϕ_{leaf} is unloaded and ϕ_{fruit} is injected.

4.2.3. Algorithmic Advantages

This specific algorithm provides three guarantees that traditional methods do not:

1. **Zero Forgetting:** Updating the Fruit Adapter cannot mathematically alter the Leaf Adapter, as they are distinct files.
2. **Gradient Isolation:** Gradients calculated for "Blossom End Rot" (Fruit) never flow into the parameters responsible for "Early Blight" (Leaf).
3. **Head Independence:** The Leaf module has a 10-dimensional output vector, while the Fruit module has a 4-dimensional output vector. The algorithm dynamically swaps the final layer to match the active adapter.

4.3. Implementation and Experimental Setup

A. Data Partitioning and Domain Definition

To validate the **Parameter Isolation** architecture, the experimental setup differs from standard mixed datasets (which combine leaves, stems, and fruits into a single pool). Instead, the data is partitioned into distinct **semantic domains**. This separation is critical to ensure that the model learns specialized features for specific plant parts without the "visual noise" or feature conflict arising from unrelated categories.

1. Module 1: Tomato Leaf Adapter

- **Domain Focus:** High-frequency texture analysis. This module is tasked with identifying surface-level pathologies characterized by discoloration, necrotic spots, and fungal patterns on the leaf blade.
- **Target Classes:** The dataset for this adapter comprises ten distinct classes, covering the full spectrum of common foliar diseases:
    1. Bacterial Spot
    2. Early Blight
    3. Late Blight
    4. Leaf Mold
    5. Septoria Leaf Spot
    6. Two-Spotted Spider Mite
    7. Target Spot
    8. Tomato Mosaic Virus
    9. Tomato Yellow Leaf Curl Virus
    10. Healthy Leaves
- **Objective:** To fine-tune the backbone's attention mechanisms to recognize surface irregularities and texture gradients specific to leaf tissues.

2. Module 2: Tomato Fruit Adapter

- **Domain Focus:** Volumetric and structural analysis. Unlike the leaf module, this expert is designed to detect deformities, shape irregularities, and deep-tissue rot on the fruit body.

- **Target Classes:** The dataset is strictly limited to fruit-centric conditions to prevent "negative transfer" from leaf features:
    1. Blossom End Rot (Physiological disorder affecting fruit shape/bottom)
    2. Anthracnose (Sunken, dark lesions on fruit surface)
    3. Fruit Cracking (Structural integumentary failure)
    4. Healthy Fruit
- **Objective:** To specialize the adapter in recognizing volumetric defects and color anomalies (e.g., blackening at the blossom end) that are morphologically distinct from foliar diseases.

B. Training Environment

The experimental validation was conducted in a high-performance cloud-based simulation environment provided by **Google Colab**. This platform was selected to leverage enterprise-grade hardware acceleration for efficient fine-tuning of the Vision Transformer backbone.

Hardware Infrastructure:

- **GPU:** The training was executed on an **NVIDIA A100 Tensor Core GPU** with **40GB of High-Bandwidth Memory (HBM2)**. This high-end accelerator allowed for larger batch sizes and faster convergence rates compared to standard consumer-grade GPUs.
- **System RAM:** High-RAM runtime environment (approx. 83GB system RAM) to handle high-resolution image pre-processing without memory bottlenecks.

Software Stack:

- **Language:** Python 3.10.
- **Deep Learning Framework: PyTorch** (with CUDA support) served as the primary tensor computation engine.
- **Model Libraries:** The implementation relied on the **Hugging Face PEFT (Parameter-Efficient Fine-Tuning) library.**

C. Data Processing To ensure compatibility with the pre-trained DINOv2 backbone, a preprocessing pipeline was applied to all input images before they entered the network.

1. **Resolution Standardization:** All raw images were resized to **256 × 256** pixels and then center-cropped to **224 × 224** pixels. This specific resolution matches the patch-embedding requirements of the Vision Transformer architecture (patch size 14 × 14).
2. **Normalization:** Pixel values were normalized using the ImageNet mean (**μ = [0.485, 0.456, 0.406]**) and standard deviation (**σ = [0.229, 0.224, 0.225]**). This step is critical because the frozen backbone expects inputs in this specific statistical distribution.
3. **Data Augmentation (Training Only):** To improve robust generalization, the training stream included random horizontal flips and slight color jittering, whereas the validation stream remained deterministic.

5. APPLICATION AND RESULTS

5.1. Application: Implementation of Modular Class-Incremental Learning

The primary application of this study is the validation of a **Class-Incremental Learning (CIL)** architecture. Unlike monolithic training approaches, which often suffer from catastrophic forgetting, this study applied a **Parameter Isolation** methodology to construct distinct, domain-specific inference modules. These modules were optimized in independent experimental runs, ensuring that the gradient updates for one biological domain did not alter the weights of the other.

The implementation resulted in two decoupled inference engines sharing a frozen **DINOv2** backbone:

Module 1: Tomato Leaf Adapter

- **Implementation:** A Low-Rank Adaptation (LoRA) module initialized specifically for **foliar texture analysis**.
- **Training Scope:** This module was optimized exclusively on the 10-class leaf dataset. The objective was to fine-tune the backbone's attention mechanism to detect high-frequency surface features such as necrosis, chlorosis, and fungal patterns (e.g., *Septoria*, *Early Blight*), independent of volumetric fruit geometry.

Module 2: Tomato Fruit Adapter

- **Implementation:** A separate LoRA module initialized to detect **volumetric abnormalities** on the fruit body.
- **Training Scope:** This module was trained on a specific subset of fruit-related defects (*Blossom End Rot*, *Anthracnose*, *Cracking*). During this training phase, the leaf adapter was physically unloaded and frozen, ensuring that the optimization for 3D fruit features occurred in a mathematically isolated parameter space.

5.2. Experimental Results

The system was evaluated based on the classification performance of each isolated adapter on its respective validation set. Quantitative analysis confirms that the parameter isolation strategy yields high-performance experts for both domains.

5.2.1. Quantitative Analysis: Tomato Leaf Adapter

Tomato Leaf Adapter demonstrated rapid convergence and high generalization capability, achieving an overall accuracy of **97.3%**. The classification report (Table 4.1) indicates robust feature extraction, with F1-scores consistently exceeding 0.95 for visually similar classes. Notably, the model achieved an F1-score of **0.969 for Early Blight** and **0.958 for Bacterial Spot**, distinguishing effectively between concentric ring patterns and water-soaked lesions.

Disease Class	Precision	Recall	F1-Score
Bacterial Spot	0.960	0.957	**0.958**
Early Blight	0.984	0.955	**0.969**
Late Blight	0.963	0.987	**0.975**
Leaf Mold	0.965	0.974	**0.970**
Septoria Leaf Spot	0.942	0.945	**0.944**
Spider Mites	0.980	0.987	**0.984**
Target Spot	0.987	0.987	**0.987**
Mosaic Virus	0.991	0.995	**0.993**
Yellow Leaf Curl Virus	0.995	0.972	**0.984**

Healthy	0.987	0.997	**0.992**
OVERALL ACCURACY			**97.3%**

Table 3: Performance Metrics - Tomato Leaf Adapter (Validation Split)

5.2.2. Quantitative Analysis: The Tomato Fruit Adapter

The Tomato Fruit Adapter achieved an overall accuracy of **98.7%** (Table 4.2). While the aggregate metrics are high, the training dynamics exhibited higher loss volatility compared to the leaf adapter run. This suggests that mapping volumetric defects (e.g., *Blossom End Rot*) via a 2D Vision Transformer requires more complex optimization than surface texture recognition. However, the high recall rates confirm the model's utility in identifying critical physiological disorders.

Defect Class	**Precision**	**Recall**	**F1-Score**
Anthracnose	1.000	0.889	**0.941**
Blossom End Rot	0.958	0.986	**0.972**
Fruit Cracking / Gray Mold	1.000	1.000	**1.000**
Healthy Fruit	1.000	0.983	**0.992**
OVERALL ACCURACY			**98.7%**

Table 4: Performance Metrics - Tomato Fruit Adapter (Validation Split)

5.3. Critical Analysis of the Study

5.3.1. Satisfactory Aspects: Resolution of Catastrophic Forgetting

The results validate the hypothesis that **Parameter Isolation** effectively resolves the stability-plasticity dilemma inherent in continual learning.

- **Architectural Stability:** The primary objective was to prevent "Catastrophic Forgetting"—the degradation of prior knowledge upon learning new tasks. By maintaining orthogonal parameter sets for the Foliar and Carpological domains, the system guarantees **zero interference**.
- **Scalability:** The successful convergence of the Fruit Adapter without accessing the Leaf Adapter's weights demonstrates that the system can be extended indefinitely (e.g., adding Root or Stem modules) with no risk to the performance integrity of existing modules.

5.3.2. Unsatisfactory Aspects: Integration and Data Constraints

While the modular components perform efficiently in isolation, the study identifies two significant limitations regarding system integration and robustness:

1. **Absence of Automated Domain Routing:** A critical architectural gap is the lack of an automated upstream classifier to determine the appropriate module for a given input. The current inference pipeline relies on **manual context switching** (i.e., the user must explicitly select the target domain). This dependency introduces a single point of failure: if a user inputs a fruit image while the Leaf Module is active, the model forces a prediction within the incorrect label space, yielding wrong results.
2. **Geometric Generalization Issues (2D vs. 3D):** The performance disparity between modules highlights a data limitation. The DINOv2 backbone is optimized for 2D texture recognition, which aligns well with leaf pathologies. However, fruit defects are fundamentally **3D volumetric** problems dependent on lighting, depth, and angle. The current fruit dataset lacks sufficient geometric diversity to fully compensate for the backbone's 2D bias, rendering the Fruit Adapter less robust to environmental variation than its Leaf counterpart.

6.CONCLUSION

This report provides an overview of our preliminary research phase to create an adaptive AI module for precision agriculture, which is still ongoing. The main goal of this first phase was to build a high-performance architectural foundation that could support the stability-plasticity paradox and cope with the limitations of mobile edge devices.

The initial outcomes of this stage highlight the advantages of the selected approach in a very clear way:

Proof of Concept and Methodological Success: The combination of DINOv2-based Vision Transformers and LoRA (Low-Rank Adaptation) has turned out to be successful in building an extremely reliable diagnostic framework which is way better than traditional CNN-based object detection. Our testing indicated that YOLOv8n, after 100 cycles, would only reach a maximum of 92.xx% accuracy while our proposed model would get to 97.88% accuracy in just 10 cycles. Such a ten times increase in learning efficiency is a strong affirmation of the possibility of hyper-fast adaptation in changing environments.

Edge Feasibility: The adoption of LoRA has not only been instrumental in cutting down the number of parameters that need to be trained by 98%, but it has also created an environment fit for the practical application of real-time updates in mobile and edge hardware without the inconvenience of going through full model retraining or consuming large amounts of energy.

Mitigation of Catastrophic Forgetting: Our parameter-isolation technique has been validated by initial tests and is allowing the model to update the classes of pathogens with the least amount of their previously acquired diagnostic information being forgotten.

Future Work and Second Semester Roadmap: This ongoing project has next semester as the transition period from experimental validations to fully integrated mobile diagnostic systems. The following objectives will be our next steps:

Dataset Expansion: Diversifying the disease and pest classes to further test the boundaries of our Class-Incremental Learning framework.

Field Optimization: Improving the analysis of the "Internal Morphological Signature" to ensure it is tolerant to varying outdoor light conditions and complex field backgrounds.

In conclusion, the first phase of the project has established a diagnostic core that is very precise and has low memory requirements. The achievements up till now have not only established but also a solid basis for the next phase of execution, which will be a scalable continual system for the digital agricultural metamorphosis of Turkey.

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APPENDICES

Appendix A

Python Code for Development of LoRA Adapters

```
from torchvision import transforms
mean, std = [0.485, 0.456, 0.406], [0.229, 0.224, 0.225]

train_transform = transforms.Compose([
    transforms.RandomResizedCrop(224, scale=(0.8, 1.0)),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(20),
    transforms.ColorJitter(brightness=0.4, contrast=0.4, saturation=0.4, hue=0.1),
    transforms.RandomAffine(degrees=0, translate=(0.1, 0.1)),
    transforms.ToTensor(),
    transforms.RandomErasing(p=0.2),
    transforms.Normalize(mean, std)
])

val_test_transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean, std)
])
```

```
from datasets import load_dataset, DatasetDict

full_ds = load_dataset("imagefolder", data_dir=DATASET_PATH)
full_ds = full_ds["train"].train_test_split(test_size=0.2, seed=SEED)
val_test = full_ds["test"].train_test_split(test_size=0.5, seed=SEED)
```

```
dataset = DatasetDict({
    "train":      full_ds["train"],
    "validation": val_test["train"],
    "test":       val_test["test"]
})


def preprocess_train(ex):
    ex["pixel_values"] = [train_transform(img.convert("RGB")) for img in ex["image"]]; return ex
def preprocess_val_test(ex):
    ex["pixel_values"] = [val_test_transform(img.convert("RGB")) for img in ex["image"]]; return ex


dataset["train"]      = dataset["train"].map(preprocess_train,      batched=True, num_proc=2,
load_from_cache_file=True)
dataset["validation"] = dataset["validation"].map(preprocess_val_test, batched=True, num_proc=2,
load_from_cache_file=True)
dataset["test"]       = dataset["test"].map(preprocess_val_test,     batched=True, num_proc=2,
load_from_cache_file=True)


for split in dataset:
    dataset[split].set_format("torch", columns=["pixel_values", "label"])


num_labels = len(dataset["train"].features["label"].names)
id2label   = {str(i): name for i, name in enumerate(dataset["train"].features["label"].names)}
label2id   = {v: k for k, v in id2label.items()}
from transformers import Dinov2ForImageClassification
from peft import LoraConfig, get_peft_model, TaskType


base_model = Dinov2ForImageClassification.from_pretrained(
    "facebook/dinov2-small",
    num_labels=num_labels,
```

```
    id2label=id2label,
    label2id=label2id
)
for param in base_model.parameters():
    param.requires_grad = False

lora_config = LoraConfig(
    r=8, lora_alpha=16,
    target_modules=["query", "key", "value", "dense"],
    bias="none",
    task_type=TaskType.FEATURE_EXTRACTION
)
model = get_peft_model(base_model, lora_config)

model.print_trainable_parameters()
device = "cuda" if torch.cuda.is_available() else "cpu"
model.to(device)
import os, json, torch, numpy as np
from transformers import TrainingArguments, Trainer, EarlyStoppingCallback

LOCAL_OUT = "/content/tomato_aug_final"
ADAPTER_OUT = "/content/drive/MyDrive/adapters/tomato_aug_final"
os.makedirs(ADAPTER_OUT, exist_ok=True)

args = TrainingArguments(
    output_dir=LOCAL_OUT,
    per_device_train_batch_size=128,
    per_device_eval_batch_size=128,
    num_train_epochs=20,
```

```
    learning_rate=5e-4,
    weight_decay=0.05,
    warmup_ratio=0.1,
    eval_strategy="epoch",
    save_strategy="epoch",
    load_best_model_at_end=True,
    metric_for_best_model="accuracy",
    greater_is_better=True,
    seed=SEED,
    bf16=torch.cuda.is_bf16_supported(),
    fp16=not torch.cuda.is_bf16_supported(),
    report_to="none",
    dataloader_num_workers=4,
    dataloader_pin_memory=True,
    logging_steps=50,
)


def compute_metrics(eval_pred):
    preds = np.argmax(eval_pred.predictions, axis=1)
    return {"accuracy": (preds == eval_pred.label_ids).mean()}


class FeatureSaveTrainer(Trainer):
    def __init__(self, *args, **kwargs):
        super().__init__(*args, **kwargs)
        self.feat_dir = os.path.join(LOCAL_OUT, "features")
        os.makedirs(self.feat_dir, exist_ok=True)

    def evaluate(self, eval_dataset=None, ignore_keys=None, metric_key_prefix="eval"):
        metrics = super().evaluate(eval_dataset, ignore_keys, metric_key_prefix)
```

```
            train_loader = self.get_train_dataloader()
        feats, labs = [], []
        self.model.eval()
        with torch.no_grad():
            for batch in train_loader:
                if "label" not in batch:                        continue
                pv = batch["pixel_values"].to(self.model.device)
                cls = self.model.base_model.dinov2(pv).pooler_output.cpu().numpy()
                feats.append(cls)
                labs.append(batch["label"].numpy())
        if feats:
            feats = np.concatenate(feats)
            labs = np.concatenate(labs)
            epoch = int(self.state.epoch)
            np.savez_compressed(os.path.join(self.feat_dir, f"epoch{epoch}.npz"),
                                features=feats.astype(np.float16), labels=labs.astype(np.int16))
        self.model.train()
        return metrics


trainer = FeatureSaveTrainer(
    model=model,
    args=args,
    train_dataset=dataset["train"],
    eval_dataset=dataset["validation"],
    compute_metrics=compute_metrics,
    callbacks=[EarlyStoppingCallback(early_stopping_patience=5)]
)


trainer.train()
```