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Vision Transformer (ViT) Implementation for Fruit Quality Assessment

Model Architecture Overview

The implemented model is a Vision Transformer (ViT) designed specifically for a fine-grained fruit quality assessment task. The ViT architecture represents a departure from traditional convolutional neural networks (CNNs) by applying a transformer-based approach to image classification.

Key Components:

1. **Patch Creation Layer**:
    - Divides input images (224×224×3) into patches of size 8×8
    - Resulting in 784 patches (28×28) per image
2. **Embedding Layers**:
    - Patch Embedding: Projects each patch into a 128-dimensional embedding space
    - Position Embedding: Adds positional information to maintain spatial relationships
3. **Transformer Encoder**:
    - 8 transformer layers with multi-head self-attention
    - Each with 8 attention heads and layer normalization
    - GELU activation function in feed-forward networks
    - Dropout rate of 0.01 for regularization
4. **Classification Head**:
    - Global average pooling to aggregate feature representations
    - MLP with two hidden layers (2048 → 1024 → 7 classes)
    - Softmax activation for final class probabilities

Model Parameters:

- Total parameters: 7,772,551 (29.65 MB)
- All parameters are trainable

Training Configuration

- **Image Size**: 224×224×3
- **Batch Size**: 32

- **Epochs**: 50 (with early stopping at epoch 43)
- **Optimizer**: AdamW with weight decay (1e-5)
- **Initial Learning Rate**: 1e-4
- **Loss Function**: Sparse Categorical Cross-Entropy
- **Random Seeds**: 42 for reproducibility

Data Augmentation:

- Rotation (up to 20°)
- Zoom (±10%)
- Width and height shifts (±10%)
- Shear transformation (10%)
- Horizontal flipping

Training Strategies:

- Class weights to handle significant class imbalance
- Learning rate reduction on plateau
- Early stopping with patience of 10 epochs
- Model checkpointing to save best weights

Dataset Analysis

The dataset focuses on banana and tomato quality classification with 7 classes:

- banana_overripe: 1,395 samples
- banana_ripe: 1,440 samples
- banana_rotten: 1,987 samples
- banana_unripe: 1,370 samples
- tomato_fully_ripened: 50 samples
- tomato_green: 334 samples
- tomato_half_ripened: 81 samples

Severe Class Imbalance:

- Imbalance ratio: 39.74 (largest/smallest class)
- Tomato classes significantly underrepresented
- Class weights applied: from 0.48 for banana_rotten to 19.02 for tomato_fully_ripened

Training Results and Analysis

Performance Metrics:

- **Final Training Accuracy**: 96.25%
- **Final Validation Accuracy**: 95.39%
- **Best Model**: Saved at epoch 41

Training Progression:

1. **Initial Phase** (Epochs 1-4):
   - Rapid improvement from 20.93% to 81.03% training accuracy
   - Validation accuracy reached 88.08% by epoch 4
2. **Mid Training** (Epochs 5-22):
   - Slower but steady improvements
   - Notable performance drop at epoch 21 (validation accuracy: 67.75%)
   - Learning rate reduced to 2e-5 at epoch 22
3. **Fine-tuning** (Epochs 23-43):
   - Two more learning rate reductions (to 4e-6 at epoch 28, 1e-6 at epoch 38)
   - Validation accuracy plateaued around 94-95%
   - Early stopping triggered after 10 epochs without improvement

Learning Dynamics:

- The learning rate scheduler effectively managed training progression
- Model showed good resilience to overfitting with validation loss generally tracking training loss
- The temporary performance drop at epoch 21 suggests the model encountered a challenging optimization landscape

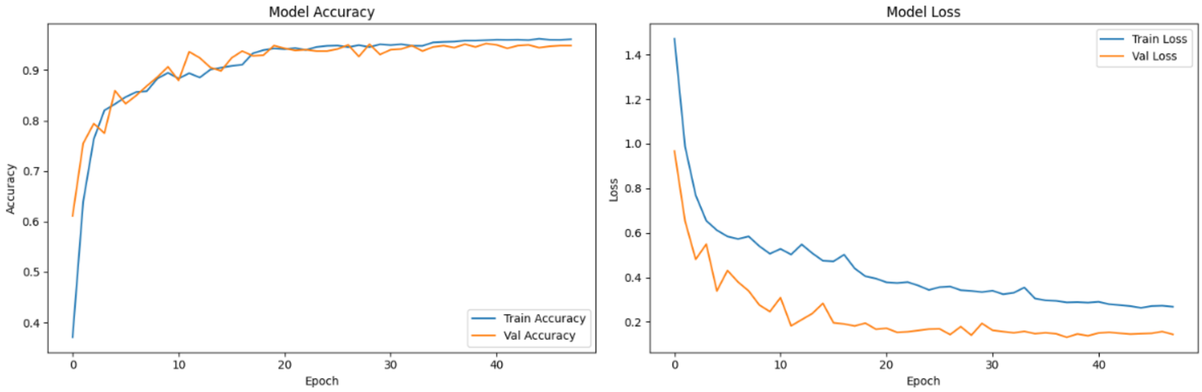
Comparison with Previous Attempts

1. **Google ViT (Pre-trained on ImageNet)**:
   - Despite leveraging transfer learning, this approach yielded inferior accuracy
   - The specialized architecture in the custom ViT proved more effective for the fruit quality task
   - Pre-trained weights may have been less relevant for the specific fine-grained distinctions required
2. **Data Augmentation to Balance Classes**:
   - Previous attempt to augment underrepresented classes to 2,200 samples each
   - This approach did not yield satisfactory accuracy
   - Current implementation with class weights appears more effective than synthetic oversampling

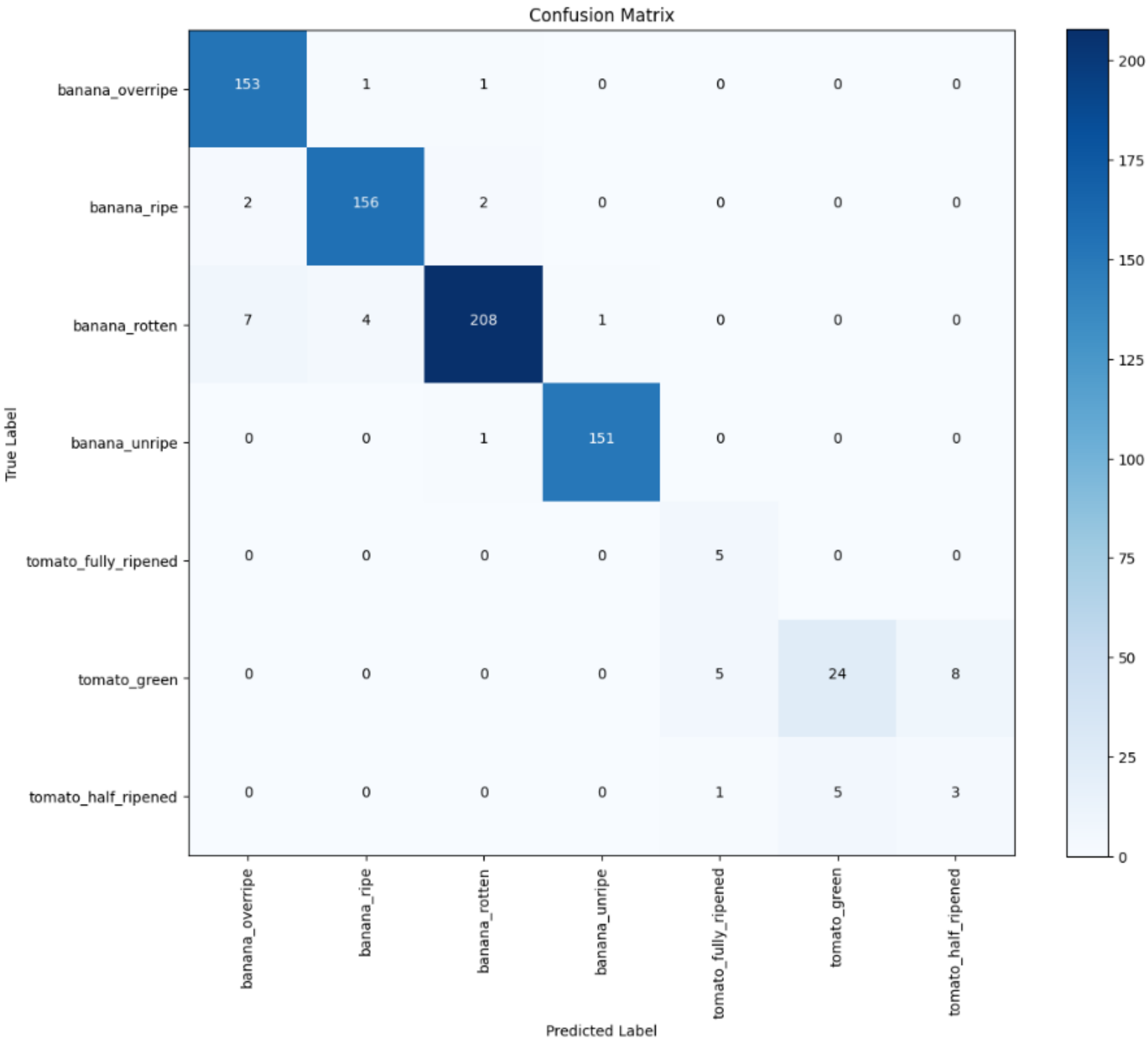
Strengths of the Current Model

1. **Custom ViT Architecture**:
   - Specifically designed for the fruit quality assessment task
   - Appropriate patch size (8×8) captures relevant texture details
2. **Effective Training Strategy**:
   - Class weights better addressed imbalance than synthetic oversampling
   - Learning rate scheduling prevented convergence to poor local minima
   - Early stopping and checkpointing ensured optimal model selection
3. **High Performance**:
   - ~95% validation accuracy shows strong generalization capability
   - Consistent performance across both banana and tomato categories despite imbalance

Model training history



Model confusion matrix



Conclusion

The custom Vision Transformer implementation demonstrates excellent performance on the fruit quality assessment task, achieving 95.39% validation accuracy despite significant class imbalance. The model successfully outperformed previous attempts using pre-trained Google ViT and data augmentation approaches. The combination of appropriate architecture design, effective handling of class imbalance through weighting, and careful training strategies contributed to the model's success.