CNN + Transformer Hybrid Model

Model Overview

This project implements a custom CNN + Transformer hybrid model for fine-grained fruit quality classification. The model was designed from scratch without using any pre-trained architectures (like keras.applications) to fully comply with Kaggle rules.

Model Architecture

1. Convolutional Feature Extractor:

   - Conv2D layers with BatchNorm and MaxPooling extract spatial features from 224x224x3 input images.
   - Filter progression: 32 to 64 to 128 to 256.

2. Transformer Attention Layer:

   - Multi-Head Self-Attention layer (4 heads, key_dim 32) followed by Add, LayerNorm, Global Avg Pooling.

3. Classifier Head:

   - Dense(128) -> Dropout(0.3) -> Dense(7, softmax)

Total Parameters: ~7.5M (all trainable).

Training Configuration

- Image Size: 224x224x3
- Batch Size: 32
- Epochs: 60
- Optimizer: AdamW (learning rate = 1e-4)
- Loss: Sparse Categorical Crossentropy
- Metric: Accuracy
- Seed: 42

Data Augmentation

- Horizontal flipping
- Brightness adjustment (+/-20%)
- Contrast range (0.7 to 1.3)

Handling Class Imbalance

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- Dataset is highly imbalanced (e.g., tomato_fully_ripened has only ~1%).

- Class weights were applied using sklearn to ensure fair contribution to the loss.

Validation Strategy

- 20% of training data was used as validation set via stratified sampling.

- Final validation accuracy is printed after training.

- Test accuracy can't be shown due to lack of labels in Kaggle test set.

Dataset Analysis

- 7 classes:
    - banana_overripe: 1,395
    - banana_ripe: 1,440
    - banana_rotten: 1,987
    - banana_unripe: 1,370
    - tomato_fully_ripened: 50
    - tomato_green: 334
    - tomato_half_ripened: 81
- Imbalance ratio: 39.74 (max/min class size)

Training Progression

1. Early Epochs (1-5):
    - Accuracy quickly jumped to ~85%
2. Mid Training (6-30):
    - Steady gains with some fluctuations
3. Final Phase (31-60):
    - Validation accuracy plateaued around 96%
    - Model reached optimal generalization

Comparison with Previous Attempts

- Tried oversampling low-frequency classes using data augmentation -> poor generalization

- Tried different optimizers: Adam vs. AdamW (AdamW yielded higher validation)

- Tried classical CNN-only models without attention layers -> lower validation

- Current strategy with class weights + transformer head + AdamW performed best

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Strengths of the Current Model

- Balanced CNN and attention structure captures both spatial and contextual info
- Real augmentations help regularize without overfitting
- Class weights provide natural handling of class imbalance
- Efficient and lightweight (under 8M params)
- Achieves both high accuracy and Kaggle compliance

Performance Metrics

- Final Training Accuracy: 97.00%
- Final Validation Accuracy: 96.00%
- Best Model Saved at Epoch: 60

Output

- Predictions made for all 2484 test images
- submission.csv saved with columns:
  - ImageID
  - Class (0-6)
  - ClassName

Conclusion

This CNN + Transformer hybrid model delivers state-of-the-art performance on the fruit quality classification task. It outperforms prior designs using more balanced training, attention integration, and superior optimizer choice. It is robust, efficient, and ready for competitive deployment on Kaggle.