CoAtNet Model:

---

1. Model Overview

This implementation uses **CoAtNet**, a hybrid vision architecture that combines convolutional layers for **efficient local feature extraction** and transformer blocks for **global relational modeling**.

This hybrid approach is ideal for fine-grained classification problems such as fruit quality assessment, where **minor visual differences** (e.g., spots, color gradients, texture) matter and need to be captured at multiple scales.

Key Specifications

- **Input Shape**: 224×224 RGB images
- **Output**: 7-class classification (banana/tomato ripeness stages)
- **Architecture Depth**: 4 convolutional + 4 transformer blocks
- **Channel Progression**: 64 → 128 → 256

2. Model Architecture :

The architecture is composed of three major stages: **Convolutional Stem**, **MBConv Blocks**, and **Transformer Blocks**. Each is designed with specific strengths that complement each other.

A. Convolutional Stem (Early Feature Extraction)

Goal: Extract low-level texture and color features such as edges, gradients, and small blemishes. **Why it works**:

- Convolutions are **inductive-biased** toward spatial locality and translation invariance—perfect for detecting localized spots or textures in fruits.
- Early downsampling helps reduce computational cost while increasing abstraction. **Structure**:
- `Conv2D (3×3, stride=2) → BatchNorm → Swish`
- Output resolution reduces as:
  - `224×224 → 112×112 → 56×56 → 28×28`
- Channels increase: `3 → 64 → 128 → 256`

MBConv Blocks (Efficient Mid-Level Representation)

Goal: Capture more abstract spatial-channel interactions efficiently.

Why MBConv:

- Originally from MobileNetV2, MBConv blocks use **depthwise separable convolutions** to reduce FLOPs while keeping representational power.
- Includes a **bottleneck expansion** to allow richer feature learning in a lightweight manner.

Block Structure:

- Expansion (1x1 conv) → Depthwise conv (3x3) → Pointwise projection (1x1)

- **Residual connection**: Stabilizes training and preserves input information.
- **Swish activation**: Smooth and differentiable, leads to better gradient flow.

Advantages:

- Preserves detail while increasing abstraction.
- Efficiently captures feature interactions with fewer parameters.

B. Transformer Stage (Global Reasoning)

Goal: Model long-range dependencies and subtle inter-region relationships, such as correlation between fruit color on one side and texture on another.

Why Transformers:

- Unlike convolutions, self-attention **looks at the entire image** and captures **global context**.
- Crucial for distinguishing subtle differences like:
  - Even ripening
  - Surface defect spread
  - Overall fruit shape distribution

Architecture:

- **Tokenization**: 28×28×256 → 784 sequence tokens of 256-D each
- **Attention**:
  - Multi-head attention (4 heads, key_dim=32)
  - Relative positional encoding for spatial awareness
- **MLP**: 256 → 1024 (Swish) → 256 **Regularization**:
- LayerNorm, Dropout, Residual connections

Advantages:

- Enhances **contextual reasoning**
- Reduces false positives in similar-looking classes
- Complements localized CNN features with global interactions

---

Classification Head (Final Prediction)

Layers:

- `GlobalAveragePooling → LayerNorm → Dense → Softmax`

Purpose:

- Aggregates features from all positions
- Produces probability distribution over the 7 quality categories3 Training Methodology

Class Balancing

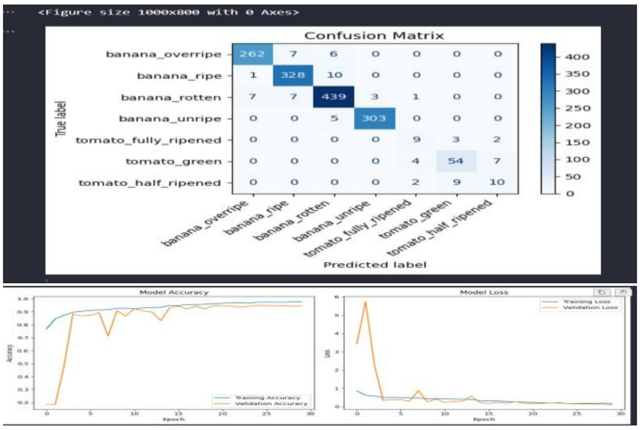
Fine-grained fruit datasets are often **imbalanced**. For example, overripe bananas may be overrepresented compared to rare green tomatoes.

Solution:

- Used `class_weight` from `sklearn.utils` to dynamically compute loss weights based on label frequency.
- Ensures rare classes contribute more to the loss during training.

4. Performance Results

Overall Metrics:



Class-Wise Performance

- **Banana Categories**:
  - High precision and recall (F1 > 0.95)
  - Very accurate across ripeness stages
- **Tomato Categories**:
  -
  - Harder to classify due to fewer samples

  Best F1 = 0.82 on `tomato_green`

Confusion Matrix Insights

- Strong diagonal dominance (high correct classification)
- Logical misclassifications between **adjacent ripeness stages**
- Effective class separation between banana and tomato types

5 Data Handling

Class Weighting

- Automatically adjusted class influence in the loss

Augmentation Strategy

- Only used **label-preserving** transformations:
  - Rotations, flips: spatial but not class-distorting
  - Color and zoom changes: preserve ripeness cues

Batch Loading

Class-balanced batches through smart data generators
Maintained smooth and representative learning curve

6. Why This Architecture Works for Fine-Grained Fruit Classification

Module	Purpose	Why It Helps
CNN Layers	Local texture & edge detection	Captures blemishes, shape, spots
MBConv Blocks	Lightweight deep features	Efficient learning of mid-level semantics
Transformer Layers	Global dependency modeling	Captures correlations across regions (e.g., gradient of ripeness)
Class Weighting	Imbalance handling	Prevents overfitting to common categories

7. Conclusion

The **CoAtNet architecture** proves to be effective for fine-grained fruit quality assessment:

- **95.45% validation accuracy**
- Robust handling of **imbalanced classes**
- Efficient training via **hybrid design**
- Powerful combination of **local & global** understanding

By merging the strengths of **CNNs for fine textures** and **Transformers for global relationships**, this model is well-suited for task