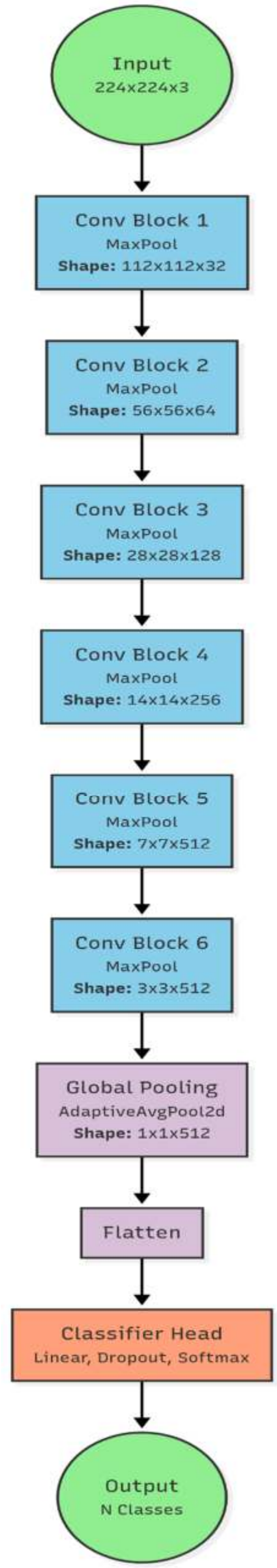
BANANA_CLASS_CNN

Objective:

Designing, deep Convolutional Neural Network from beginnning for the task of banana variety classification. The architecture is a classic sequential design optimized for learning a rich set of features.



Justification of Design Choices:

Deep 6-Block Architecture: The model uses six convolutional blocks. This deep structure allowing network to learn progressively more difficult features, from simple edges in early layers to the distinct shapes and textures of different banana varieties in later layers.

Progressive Channel Deepening: The number of feature channels doubles after each pooling layer (32 → 64 → ... → 512). This provides the model with greater capacity to capture complex details as the various dimensions.

Batch Normalization: Every convolutional layer is followed by BatchNorm2d. This is a critical regularization technique that stabilizes training, accelerates convergence, and reduces the model's sensitivity to the initialization of weights.

ReLU Activation & Softmax Output: The ReLU activation function is used for its computational efficiency and ability to prevent the vanishing gradient problem. The final Softmax layer converts the model's raw output scores into a probability distribution across the classes.

Adaptive Pooling & Dropout: The classifier head uses AdaptiveAvgPool2d to drastically reduce the number of parameters and make the model robust to input size variations. This is followed by a Dropout layer with a 50% rate, which is a powerful technique to prevent overfitting by randomly ignoring a subset of neurons during training.

Key Hyperparameters:

- **Image Size:** (224, 224)
- **Batch Size:** 32
- **Optimizer:** AdamW
- **Learning Rate:** 0.001
- **Loss Function:** CrossEntropyLoss
- **Regularization:** Dropout (p=0.5), Weight Decay (1e-4), BatchNorm, TrivialAugmentWide

BANANA_RIPE_CNN

Objective:

To design a unique, deep Convolutional Neural Network from scratch for the task of banana ripeness detection. The architecture is a robust sequential design with regularization integrated directly into the feature extractor.

Justification of Design Choices:

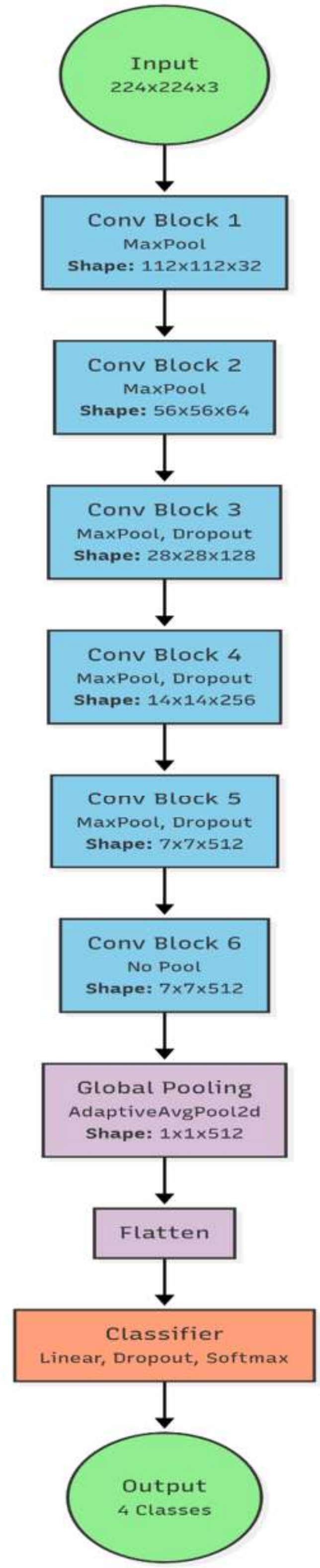
Deep 6-Block Architecture: A deep stack of six convolutional blocks is used to effectively learn the subtle visual cues that define banana ripeness, such as the transition from green to yellow, the appearance of sugar spots, and the browning of the peel.

Integrated Regularization: To aggressively combat overfitting, this model incorporates Dropout layers directly within the later stages of the feature extractor (p=0.2 to p=0.4). This technique regularizes the feature learning process itself, not just the final classification, forcing the model to develop more robust and less co-dependent feature representations.

Batch Normalization: BatchNorm2d is applied after every convolution to ensure stable gradients and faster, more reliable training. This is essential for a deep network to learn effectively.

ReLU & Softmax: The ReLU activation provides non-linearity efficiently, while the final Softmax layer ensures the model's output is a set of probabilities, making the predictions interpretable.

Efficient Classifier Head: The use of AdaptiveAvgPool2d creates a modern, lightweight classifier. It summarizes the spatial features from the final convolutional block, which is then passed to a dense layer with a final Dropout of 50% for one last stage of regularization before the output.



Key Hyperparameters:

- **Image Size:** (224, 224)
- **Batch Size:** 32
- **Optimizer:** AdamW
- **Learning Rate:** 0.001 (with CosineAnnealingWarmRestarts scheduler)
- **Loss Function:** CrossEntropyLoss
- **Regularization:** Dropout (p=0.2-0.5), Weight Decay (1e-4), BatchNorm, TrivialAugmentWide