**Introduction**

This project develops a convolutional neural network to classify banana ripeness levels. The goal is to help grocery stores monitor produce conditions and decide when to restock or revisit a section. Automating ripeness detection supports better delivery scheduling and reduces manual checks. The dataset includes labeled images organized into training, validation, and test sets. Each image belongs to a ripeness class and is used to train and evaluate the model.

**Method**

Pre-Labeled images were sourced from Kaggle ([Link](https://www.kaggle.com/datasets/shahriar26s/banana-ripeness-classification-dataset/data)), and resized to 224 × 224 pixels,. Two preprocessing pipelines were used. Training data were cast to float32, augmented with random flips, rotations, and zooms, then normalized by 1/255. Validation and test data were only cast and normalized.

A banana with a few marks

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The model is a sequential CNN. It includes three convolutional layers with 32, 64, and 128 filters, followed by ReLU activations and pooling layers. A global average pooling layer reduces the output to a flat vector, followed by a dense layer with 128 units, and a final dense layer with SoftMax to output class probabilities.

A screen shot of a black board with white text

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The design allows the model to detect color and texture changes across ripeness levels using a basic but effective structure. The model uses the Adam optimizer and sparse categorical cross-entropy loss. Accuracy is tracked during training. Training used batches of size 32, up to 10 epochs, with early stopping based on validation accuracy. The model restored the best weights and saved checkpoints during training.

**Outcome**

The training process showed consistent improvement in accuracy and reduction in loss. Validation accuracy reached about .92 , and validation loss was around 0.22.

A graph of a line and a line

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With more compute power, we would train for many more epochs, but because this was trained on a macbook air, we stuck with batches of 200 images for 10 epochs. That said, we reached satisfactory performance after about 40 minutes of training.

On the test set, the model has a macro-avg F1score of .92 with precision and recall hovering right around 93%. This performance was reltaively constent across the four classes with ripe having the lowest precision, and rotten having the lowest recall.

A screenshot of a computer screen

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We can dive deeper by looking at the confusion matrix for each class of banana ripeness.

A diagram of a confusion matrix

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Here we see that not only is ripeness classification accurate, but when bananas are misclassified, most of the time it is often from 1 level of ripeness to the adjacent level. This further increases our trust in the mode.

**Conclusion**

This model successfully classifies banana ripeness and does correctly > 90% of the time. With more computing power, and exploration this performance could be augmented, but is satisfactory for the time being. This would be a great step for grocery stores to get ahead of inventory management and continue to improve their delivery planning.