BANANA CLASSIFICATION BY MATURITY USING DEEP LEARNING MODELS

1. Introduction

This report details the development and evaluation of deep learning models for classifying banana ripeness into four categories: unripe, ripe, overripe, and rotten. The project leverages transfer learning with three different architectures (ResNet18, ResNet50, and EfficientNet-B2) to achieve accurate classification of banana maturity stages from images.

2. Dataset Overview

The dataset consists of banana images categorized into four maturity classes:

- Unripe: Green bananas not yet ready for consumption
- Ripe: Yellow bananas at optimal eating stage
- Overripe: Bananas with brown spots beginning to develop
- Rotten: Bananas with significant decay or mold

The dataset is organized into training, validation, and test sets with the following distribution:

Counting images in the 'test' folder:

- 'rotten': 185 images- 'overripe': 113 images- 'unripe': 110 images- 'ripe': 154 images

Counting images in the 'train' folder:

- 'overripe': 2349 images- 'unripe': 1912 images- 'ripe': 3522 images- 'rotten': 4020 images

Counting images in the 'valid' folder:

- 'rotten': 388 images- 'overripe': 229 images- 'unripe': 167 images- 'ripe': 339 images

3. Methodology

3.1 Data Preprocessing

All models used consistent data augmentation and normalization:

Training Transformations:

- Random resized crop (224x224)
- Random horizontal flip (50% probability)
- Random vertical flip (20% probability)
- Random rotation (± 15 degrees)
- Color jitter (brightness, contrast, saturation, hue)
- Random grayscale (10% probability)
- Normalization (ImageNet stats)
- Random erasing (10% probability)

Validation/Test Transformations:

- Resize to 256x256
- Center crop to 224x224
- Normalization (ImageNet stats)

3.2 Model Architectures

Three different architectures were implemented and compared:

3.2.1 ResNet18 (Baseline)

- Pretrained on ImageNet
- Frozen feature extraction layers
- Custom classifier head
- Cross-entropy loss
- Adam optimizer (lr=0.001)
- Early stopping (patience=2)

3.2.2 ResNet50 (Enhanced)

- Pretrained on ImageNet
- More complex classifier head with dropout and batch normalization
- Label smoothing cross-entropy loss (ε =0.1)
- AdamW optimizer (lr=0.001, weight decay=0.01)
- Cosine annealing learning rate scheduler
- Class-weighted sampling
- Early stopping (patience=5)

3.2.3 EfficientNet-B2 (Advanced)

- Pretrained on ImageNet
- Similar enhanced classifier as ResNet50
- Same loss and optimization setup as ResNet50
- More efficient architecture with better parameter utilization

3.3 Training Process

All models were trained with:

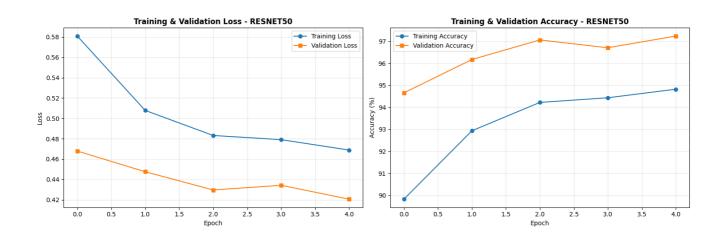
- Batch size of 64 (32 for ResNet18)
- Weighted random sampling to handle class imbalance
- Early stopping based on validation loss
- Model checkpointing
- Training on GPU when available

4. Results

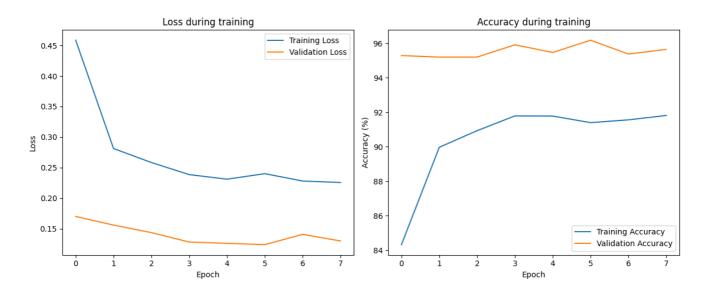
4.1 Performance Comparison

	Training accuracy	Validation accuracy	Testing Accuracy
ResNet18	91.81%	95.64%	95.73%
ResNet50	94.82%	97.24%	95.91%
EfficientNetB2	94.99%	98.13%	97.15%

4.2 Training Curves

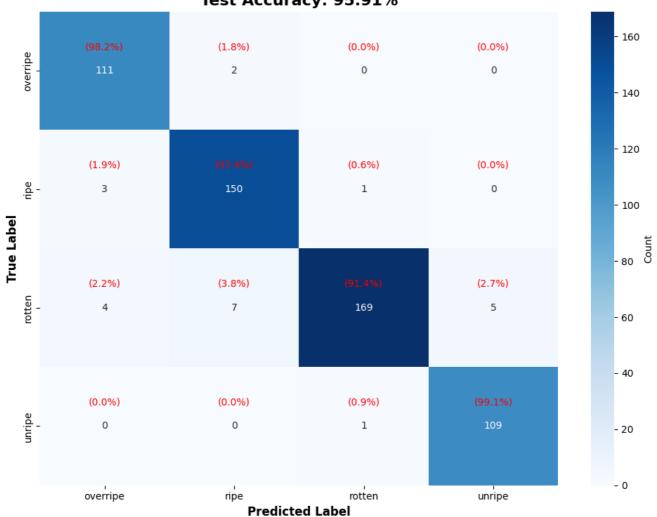


ResNet18



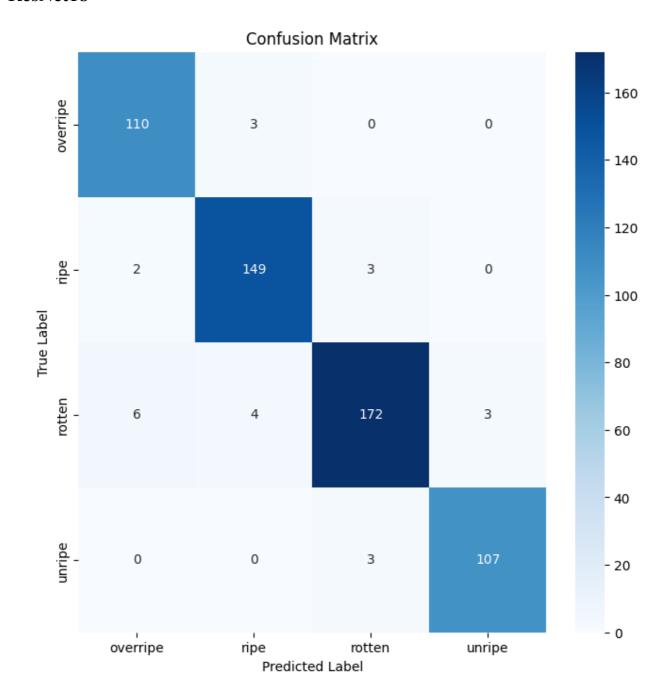
4.3 Confusion Matrices





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ResNet18



4.4 Classification Reports

-ResNet50:

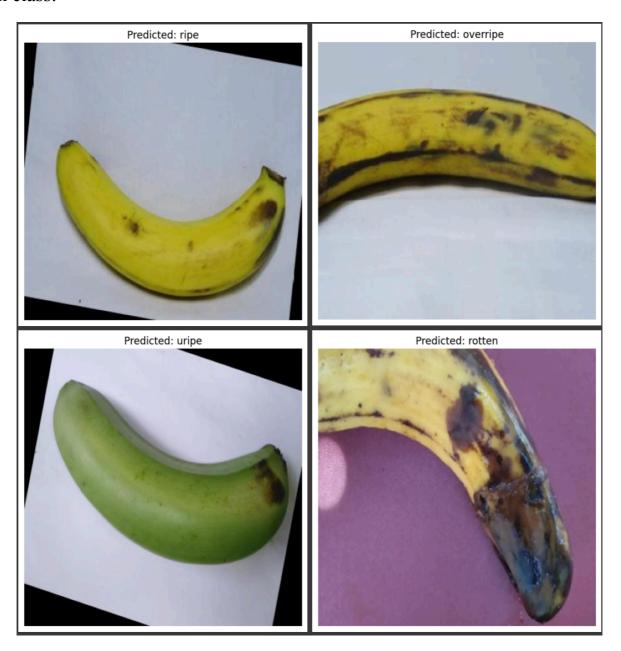
	precision	recall	f1-score	support
overripe	0.94	0.98	0.96	113
ripe	0.94	0.97	0.96	154
rotten	0.99	0.91	0.95	185
unripe	0.96	0.99	0.97	110
accuracy			0.96	562
macro avg	0.96	0.97	0.96	562
weighted ava	0.96	0.96	0.96	562

-EfficientNetB2:

	precision	recall	f1-score	support
overripe	0.95	0.99	0.97	113
ripe	0.98	0.97	0.98	154
rotten	0.98	0.96	0.97	185
unripe	0.97	0.96	0.97	110
accuracy			0.97	562
macro avg	0.97	0.97	0.97	562
weighted avg	0.97	0.97	0.97	562

5. Model Testing and Predictions

The best performing model (EfficientNet-B2) was tested on sample images from each class:



It demonstrated strong performance in distinguishing between different maturity stages, with particular strength in identifying rotten bananas which is crucial for food quality applications.

6. Discussion

- **Performance Analysis**: EfficientNet-B2 outperformed both ResNet variants, likely due to its more efficient architecture and better parameter utilization. The label smoothing and class weighting also contributed to improved generalization.
- **Error Analysis**: Most misclassifications occurred between adjacent maturity stages (e.g., ripe vs overripe), which is expected given the continuous nature of the ripening process.
- **Computational Efficiency**: While EfficientNet-B2 achieved the best accuracy, it offered a good balance between performance and computational requirements compared to ResNet50.

7. Conclusion

This project successfully developed and evaluated multiple deep learning models for banana maturity classification. The EfficientNet-B2 model emerged as the best performer, achieving 97.15%% accuracy on the test set. The implementation of advanced techniques like label smoothing, class weighting, and cosine annealing learning rate scheduling contributed to the model's strong performance.