Banana state estimation using Convolutional Neural Networks for waste reduction

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Introduction

Almost 59 million tonnes of food waste amounting to 131kg per person are generated yearly in the EU, according to the Eurostat report on food waste released in 2022.
More than half of the total food waste is generated by households and an additional 15% is generated by food service and retail combined.

Introduction

This has impacts on:

- Carbon emissions
- Prices
- Health
- Processed perishable foods industry

Motivation

Reduce industrial and domestic perishable food waste.

Research question

How can a Convolutional Neural Network (CNN) be used to perform an external analysis of bananas to estimate their state?

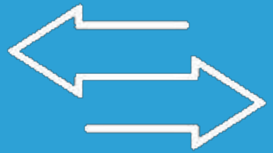
State of research

Recent studies have applied Artificial Intelligence techniques to classify fruits as either fresh or rotten. In particular, Convolutional Neural Networks(CNN) have been employed and were found to be a viable option. Specifically, the ResNet50 architecture was found to be very well performing

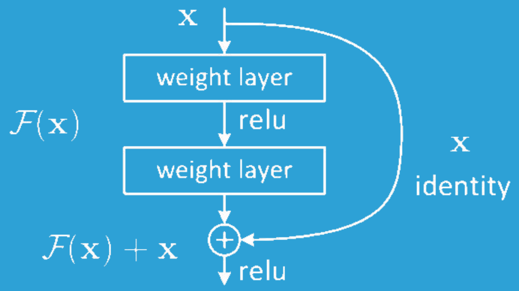
The authors of one of these studies on binary classification suggest that models could be trained to classify different levels of "rottenness".

State of research

How to train a deep residual CNN with limited data



Transfer learning



Residual block

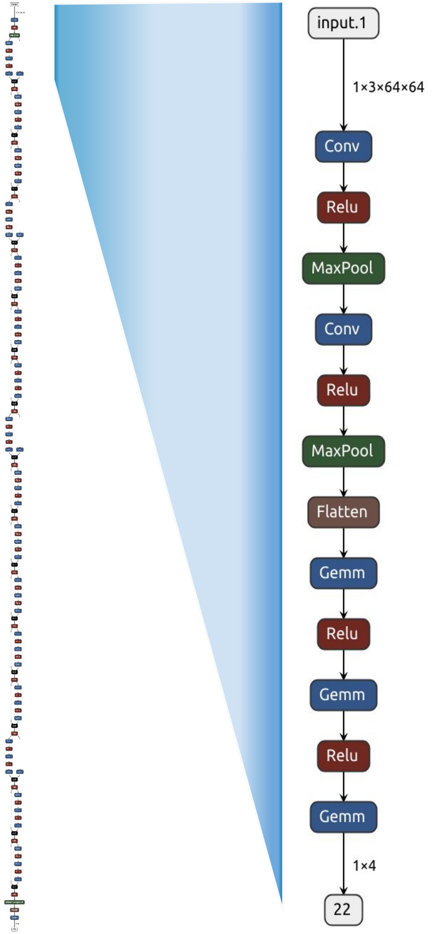
K. He, X. Zhang, S. Ren, and J. Sun. Deep Residual Learning for Image Recognition.

The goal

Classify bananas according to their **state** as **either:**

unripe - ripe - overripe - rotten

This allows to monitor the state of food (before it becomes waste)



ResNet50 CustomCNN

Methods

CustomCNN

- Convolutional Neural Network
- 7 layers - 500k parameters

ResNet50

- Deep Residual Convolutional Neural Network
- Transfer Learning
- 50 layers - 23.9 million parameters

Methods

Perform a **grid search** to select the optimal **hyperparameters**

The number of epochs is subject to early-stopping and capped at 30

Architecture	CustomCNN ResNet50
Learning Rate	0.001 0.0005 0.0001
Batch size	5 10 20

Methods

Perform a grid search to select the optimal hyperparameters

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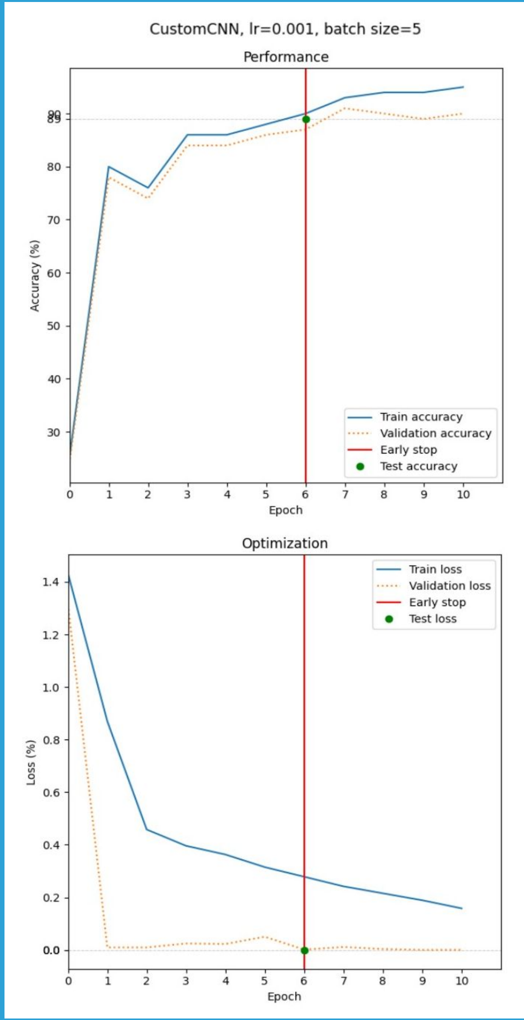

Original Dataset

TRAIN / TEST SPLIT	Training Set 87% 16k images	Validation Set 8% 1.5k images	Testing Set 4% 757 images

PREPROCESSING	**Auto-Orient:** Applied **Resize:** Stretch to 416×416
AUGMENTATIONS	**Outputs per training example:** 3 **Flip:** Horizontal, Vertical **Crop:** 0% Minimum Zoom, 20% Maximum Zoom **Brightness:** Between -25% and +25% **Noise:** Up to 5% of pixels **Cutout:** 4 boxes with 15% size each
DETAILS	**Classes:** freshripe - freshunripe - unripe - ripe - overripe - rotten **Multi-label:** Yes

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DETAILS

Classes: freshripe - freshunripe - unripe - ripe - overripe - rotten
Multi-label: Yes

Final Dataset

TRAIN / TEST SPLIT

Training Set 70%	Validation Set 15%	Testing Set 15%
~9k images	~2k images	~2k images

ADDITIONAL OPERATIONS

Unify splits
Merge classess: Freshripe → ripe & freshunripe → unripe
Remove multi-label records
Fix umbalance: Undersample the "ripe" class and oversample the other classes to match
Split:70/15/15 with random sampling

Results

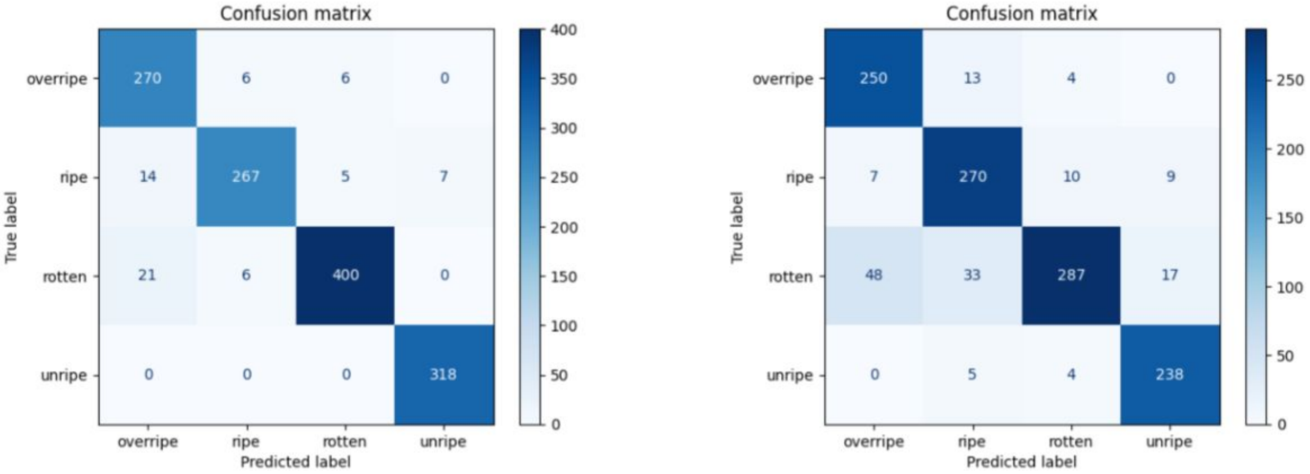
	Learning rate	0.001	0.0005	0.0001	0.001	0.0005	0.0001	0.001	0.0005	0.0001
	Batch size	5	5	5	10	10	10	20	20	20
	Architecture	CustomCNN								
Class accuracy	Unripe	94.6%	96.3%	96.5%	91.1%	95.9%	96.1%	97.4%	94.6%	97.4%
	Ripe	89.5%	80.5%	93.0%	97.5%	98.2%	93.6%	83.6%	96.1%	86.3%
	Overripe	89.6%	76.5%	88.6%	89.6%	91.9%	89.4%	61.4%	82.6%	82.6%
	Rotten	84.0%	91.2%	68.5%	60.3%	54.9%	59.7%	81.9%	62.8%	59.9%
	Accuracy	89%	86%	86%	84%	85%	84%	81%	83%	81%
	Class accuracy SD	4	9	13	17	20	17	15	15	16
	Loss	0.0002	0.00005	0.0001	0.0659	0.0316	0.1543	0.1919	0.1378	0.2129
	Epochs	6	6	7	5	7	23	5	8	27
		Res50								
Class accuracy	Unripe	97.8%	97.6%	97.8%	95.9%	97.4%	96.1%	98.0%	97.8%	98.0%
	Ripe	95.5%	98.0%	95.1%	95.9%	97.7%	92.8%	95.7%	97.1%	95.7%
	Overripe	96.6%	97.5%	93.2%	95.3%	95.6%	93.0%	95.6%	94.5%	95.6%
	Rotten	94.0%	90.7%	90.1%	94.0%	93.4%	87.7%	92.6%	91.2%	92.6%
	Accuracy	95%	95%	94%	95%	96%	92%	95%	95%	95%
	Class accuracy SD	2	3	3	1	2	3	2	3	2
	Loss	0.0014	0.0045	0.0321	0.0024	0.0086	0.1751	0.0667	0.0523	0.0667
	Epochs	4	5	8	3	4	9	4	5	4

Table 1: Results of the grid-search optimization

BEST

ResNet50
LR: 0.0005
BatchSize: 10

Results



(a) Best ResNet50 model

(b) Best CustomCNN model

Fig. 4: Confusion matrices for the classification on the test set

Analysis

The results appear to generalize to the test set

Randomness at epoch 0 for CustomCNN is found as expected

Tendency to misclassify an image and its relative augmentations and eventual up-sampling

Limitations

- **Randomness** may be affecting results.
- Furher **optimization** is likely possible.
- An external analysis may yield **inaccurate estimates.**
- The obtained model is very **specific to the dataset.**

Conclusion

This study showed how to apply CNNs to the task of perishable food state classification.

As suggested in previous studies, models trained with the ResNet50 architecture, initialized with pretrained parameters were successful and especially well-performing.

Future Work

- Run the grid search experiments multiple times and average the results to account for randomness.
- Adapt to multiple fruits and vegetables for domestic appliances (smart pantry/fridge).
- Build a more varied dataset and experiment with techniques(e.g. background reduction) to build a more robust and general model.

barajasaway.ddns.net:8080/resnet50

ResNet50