A Neural Network Approach to Classifying Banana Ripeness

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Introduction

- Interested in classifying fruit ripeness using machine learning methods.
- Fruit ripeness has been studied previously through image segmentation methods (Dadwal and Banga, 2012).
- Banana ripeness was previously studied by Saad et al. (2009) and Paulraj et al. (2009) through neural network methods.
- More than just bananas: aim to improve upon previous work by incorporating non-banana objects.
- Previous data set unavailable; will establish our own data set.

Data Collection

- Took pictures of bananas and non-banana objects.
- Lighting, camera (Canon S90) and background were controlled.
- Used 12 unique bananas at various stages to represent the three stages ripeness: unripe, ripe and overripe.
- Non-banana objects: green pepper, apple, tomato, lemon, lime mushrooms, broccoli, potato and pears.
- Pictures were resized and cropped to 256×256.
- Incorporated each picture at 0°, 90°, 180° and 270° of rotation to increase the number of pictures in the data set by four fold.
- Total of 928 images generated.

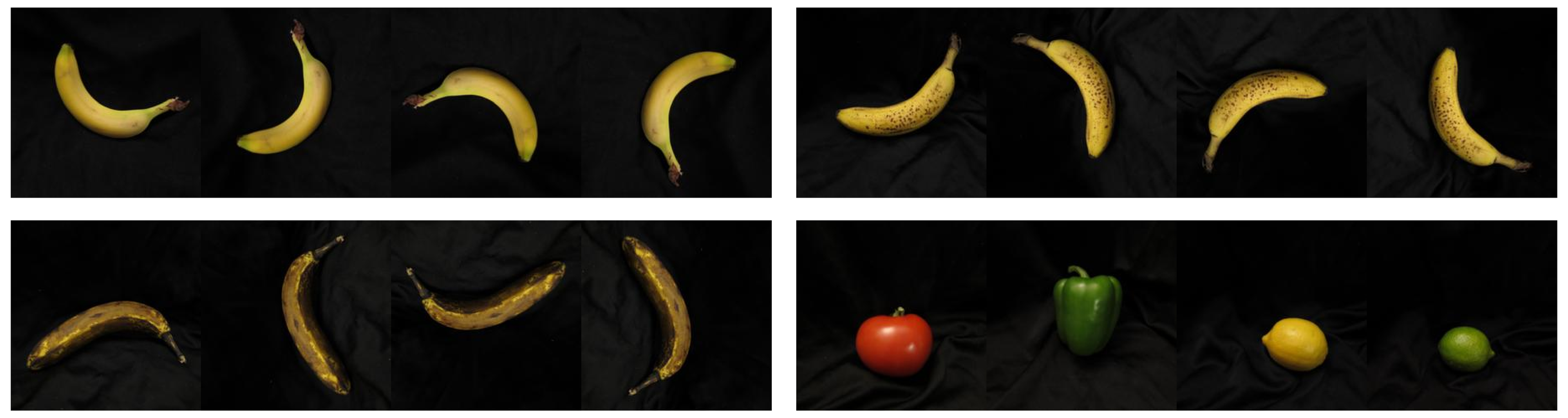

Figure 1: Upper left: unripe bananas. Upper right: ripe bananas. Lower left: overripe bananas. Lower Right: non-banana objects.

Methodology

- Extract features using pre-trained convolution neural network (CNN) from data set and classify them with support vector machine (SVM).
- Caffe (Jia et al., 2014): deep learning framework for using AlexNet.
- AlexNet (Krizhevsky et al., 2012): a pre-trained CNN for features extraction.
- SciKit Learn (Pedregosa et al., 2011): a Python library of machine learning algorithms.
  - Applied C-Support Vector Classification (*sklenar.svm.svc*) to the extracted features for classification.
  - Linear, RBF, sigmoid and polynomial kernels were compared.
  - Parameters optimization through exhaustive grid search (*sklearn.grid_search*).
- Each set of four rotated pictures were either in the train or test set.
- Workflow of this project is shown as a flowchart in Figure 2

Workflow

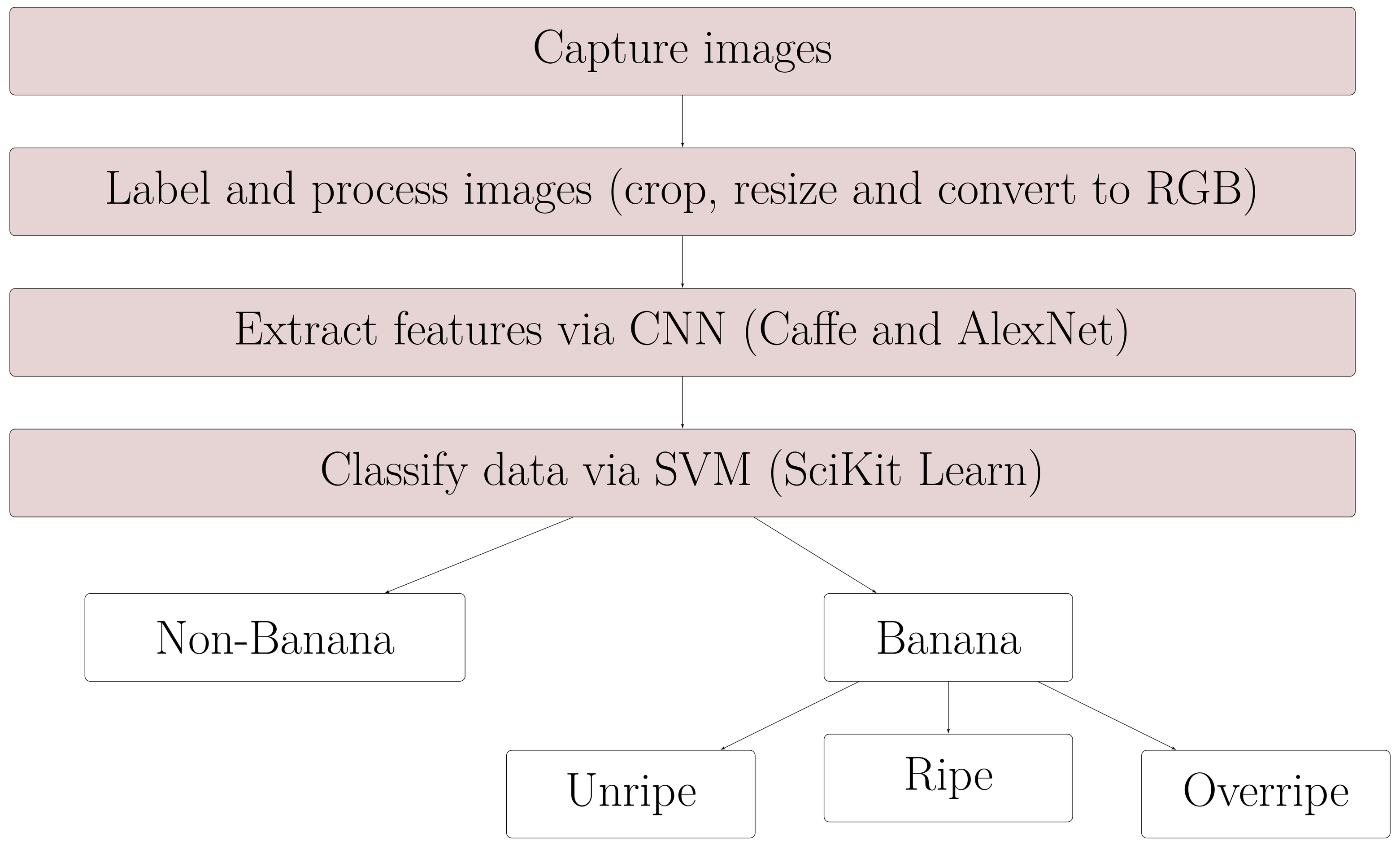

Figure 2: A flow chart of project development.

Features Extraction via AlexNet

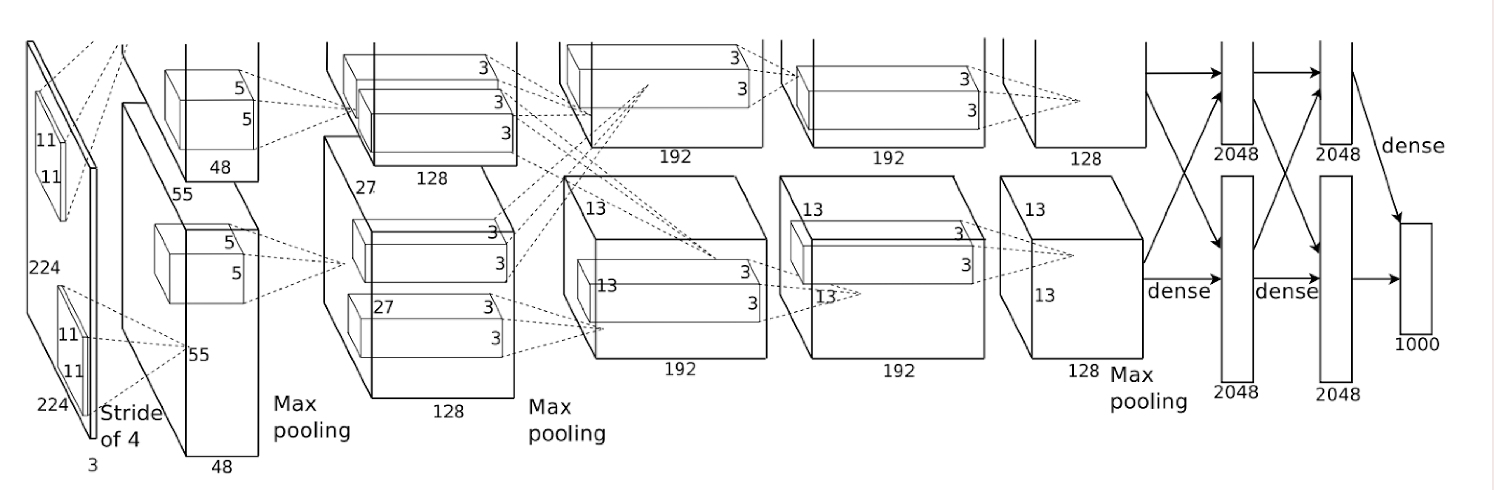

Figure 3: Architechture of AlexNet.

- AlexNet: five convolutional layers and three fully connected layers.
- Originally trained to classify images for the ILSVRC-2012 challenge.
- Extract representation of data set from last three layers (FC6, FC7 and FC8).
- Internal representations at these layers are vectors of length 4096 (FC6, FC7) or 1000 (FC8).

Results

- Tested various kernel methods from SciKit Learn's SVM library.
- Experimental results are shown in Tables 1 and 2

Table 1: Overall percentage of correctly classified objects from training and testing of SVM models with various kernels. Features were obtained from FC6, FC7 and FC8 exits of AlexNet. (Lin = linear, RBF = radial basis function, Sig = sigmoid, Poly = polynomial)

	Training Results				Testing Results			
	Lin	RBF	Sig	Poly	Lin	RBF	Sig	Poly
FC6	0.942	1.000	0.266	0.911	0.821	0.878	0.218	0.814
FC7	0.876	1.000	0.266	0.872	0.788	0.862	0.218	0.804
FC6	0.768	0.998	0.266	0.807	0.676	0.843	0.278	0.696

Results

Table 2: Percentage of objects correctly classified based on banana, ripeness and non-banana objects. Features were obtained from FC6, FC7 and FC8 exits of AlexNet. (Lin = linear, RBF = radial basis function, Sig = sigmoid, Poly = polynomial)

	Banana as Banana				Ripeness				Object as Object			
	Lin	RBF	Sig	Poly	Lin	RBF	Sig	Poly	Lin	RBF	Sig	Poly
FC6	0.946	0.953	1.000	0.958	0.862	0.902	0.288	0.885	0.829	0.934	0.000	0.711
FC7	0.924	0.945	1.000	0.932	0.885	0.901	0.288	0.895	0.697	0.882	0.000	0.711
FC8	0.864	0.924	1.000	0.877	0.804	0.890	0.2880	0.826	0.618	0.908	0.000	0.605

Results Summary

- (RBF, FC6) outperformed all other classifiers with 100.0% accuracy in training and 87.8% accuracy in testing.
- (RBF, FC6) improved the performance of Saad et al. (2009) in classifying banana ripeness with significantly larger data set.
- Sigmoid kernel classified every object as banana; 100% accuracy in classifying banana but 100% error on all non-banana objects.

Conclusion

- Successfully enhanced previous work by adding non-banana objects.
- Future: generalize ripeness detection to other fruits and vegetables.
- Industrial application: automatic large scale sorting.
- Mobile app for visually disabled: find the ripeness of fruits and vegetables via phone camera.
- Code and data set available at bit.ly/BananaRipe

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