A Neural Network Approach to Classifying Banana Ripeness

Kyle Demeule
Department of Computing Science
Faculty of Applied Sciences
Simon Fraser University
8888 University Drive
kdd2@sfu.ca

Bernard S Chan
Department of Computing Science
Faculty of Applied Sciences
Simon Fraser University
8888 University Drive
bernardc@sfu.ca

Saeed Soltani
Department of Computing Science
Faculty of Applied Sciences
Simon Fraser University
8888 University Drive
saeeds@sfu.ca

Abstract

In this paper, a new technique to detect the banana and its ripeness is introduced. This paper includes the methods and experiments that were implemented in the project. Some of the techniques that were used in this project includes classifying images by support vector machines in linear, radial basis functions and sigmoid functions. Also, we explain the optimization methods that used to improve the accuracy and decrease the number of features.

1 Introduction

Traditionally, humans detect ripeness of fruit through sight, odour, taste and touch. While people and animals are naturally equipped with these senses, machines are not, so automating fruit ripeness detection is a difficult task. Given that odor sensors and image processing are more reliable and developed than taste and touch, machine learning research in detecting fruit ripeness have been based around odor and and sight. Through different type of odour sensors, Llobet et al. [1999] and Li et al. [2007] collected smell information on ripening bananas and apples. Then, they applied various supervised classifier to classify their states.

Instead of odour, we are interested in integrating imaging and deep learning techniques to classify the ripeness of bananas. Based on reviews by Dadwal and Banga [2012] and Kodagali and Balaji [2012], typical computer vision based ripeness detection methods are based on histogram matching or image segmentation. For example, Paulraj et al. [2009] proposed a histogram-based neural network classifier for evaluating ripeness banana He derived that by using the histograms that were obtained from banana pictures as a feature vector and sending that as an input to neural networks, it could classify the imported banana as ripe or unripe.

The ripeness recognition rate for his algorithm is 96%. However, this model does not distinguish the non-banana from banana and would only predict the ripeness. In this project, our aim was to implement a new method that could firstly detect whether the imported picture contains any banana and secondly detect the ripeness of banana based on the its skin color. Our approach to this issue is to perform feature extraction of images by using convolutional neural networks and constructing support vector machine classification model that could classify an object by detecting whether it is banana or non-banana and recognize the ripeness, if it is a banana. This model could be very helpful in helping disabled people to detect the ripeness of bananas. In addition, it could become handy in industry for large scale sorting.

2 Background

- literuatre review on fruit ripeness
- literature review on neural network, deep learning, AlexNet
- introduction to technolgies used (Caffe, ScikitLearn)

3 Methodology

For this project, we created our own data set on banana and non-banana objects because the previous data sets from Saad et al. [2009] and Paulraj et al. [2009] were not available. After establishing our own data set, we extracted the features of the images using a pre-trained convolution neural network. The Caffe deep learning frame work by Jia et al. [2014] allowed us to access from many existing models. Given that we have a visualization task with different types of objects, we chose AlexNet by Krizhevsky et al. [2012] to extract the features. After obtaining the features of the images, we used the SVM library provided in SciKit Learn [Pedregosa et al., 2011] to classify the objects. A workflow of this project is shown as a flowchart in Figure 1. In this section, we will discuss the details in each step of our work.

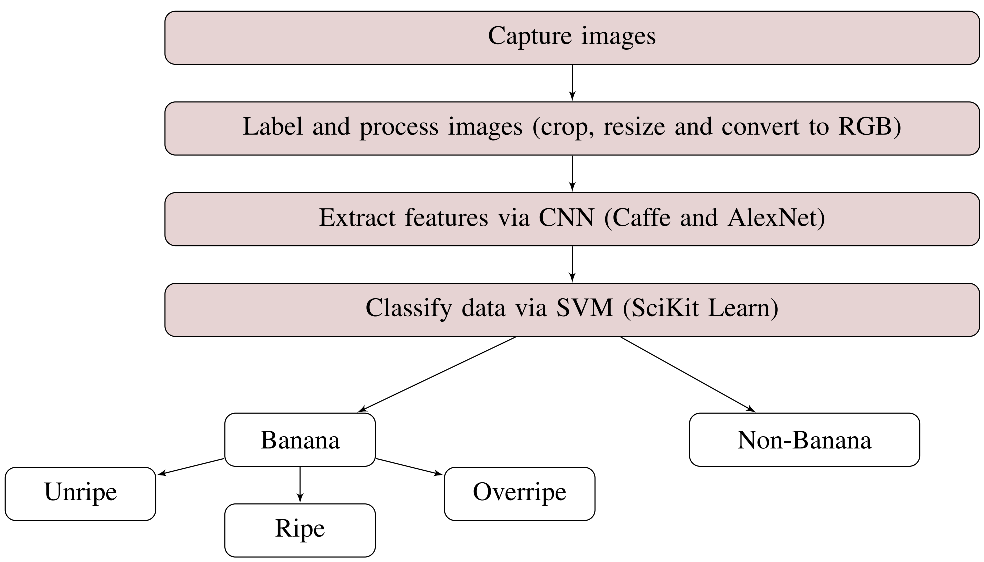

Figure 1: A flow chart of project development.

3.1 Generating and Preparing the Data set

Since the data sets used by Saad et al. [2009] and Paulraj et al. [2009] were not publicly available, we decided to create on our own data set. Controlling for lighting, background and camera (Canon S90), we took pictures of banana and various non-banana objects. After the pictures were taken, we incorporated each picture at 0°, 90°, 180° and 270° of rotation to increase the number of pictures in the data set by four fold. Also, there were equal number of pictures for each of the four labels: unripe banana, ripe banana, overripe banana and non-banana. For the banana data set, twelve unique bananas were used. We used apples, tomatos, lemons, limes, mushrooms, broccolis, potatos, pears and green peppers as non-banana objects. In total, there were 928 images generated for the data set and sample pictures of this data set are shown in Figure 2. After obtaining the data set, we used various Python scripts to standardize the images so that each one is resized and cropped to 256×256 pixels. Furthermore, each picture is decomposed into the RGB channels for features extraction.

Figure 2: Upper left: unripe bananas. Upper right: ripe bananas. Lower left: overripe bananas. Lower Right: non-banana objects.

3.2 Features Extraction via AlexNet

- Caffe [Jia et al., 2014]: deep learning framework for using AlexNet.
- AlexNet: five convolutional layers and three fully connected layers.
- AlexNet [Krizhevsky et al., 2012]: a pre-trained CNN for features extraction.
- 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).

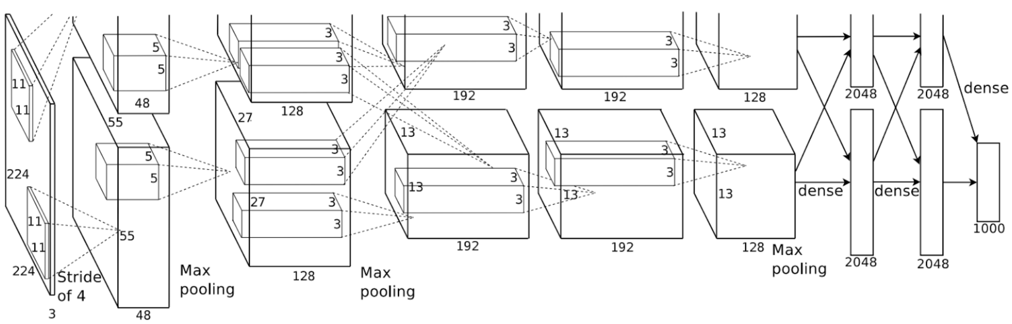

Figure 3: Architechture of AlexNet.

3.3 Classification

- Each set of four rotated pictures were either in the train or test set.
- 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*).

4 Results

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

- (RBF, FC6) outperformed all other classifiers with 100.0% accuracy in training and 87.8% accuracy in testing.

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
FC8	0.768	0.998	0.266	0.807	0.676	0.843	0.278	0.696

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

- (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.

5 Conclusion and Future Work

- 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

Acknowledgments

We thank our TA Zhiwei (Lucas) Deng for his guidance on using Caffe as well as AlexNet and Dr. Mori for his insights on solving this problem.

References

Meenu Dadwal and VK Banga. Color image segmentation for fruit ripeness detection: A review. In *2nd International Conference on Electrical, Electronics and Civil Engineering (ICEECE'2012) Singapore April*, pages 28–29, 2012.

Yangqing Jia, Evan Shelhamer, Jeff Donahue, Sergey Karayev, Jonathan Long, Ross Girshick, Sergio Guadarrama, and Trevor Darrell. Caffe: Convolutional architecture for fast feature embedding. *arXiv preprint arXiv:1408.5093*, 2014.

Jyoti A Kodagali and S Balaji. Computer vision and image analysis based techniques for automatic characterization of fruits–a review. *International Journal of Computer Applications*, 50(6), 2012.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.

Changying Li, Paul Heinemann, and Richard Sherry. Neural network and bayesian network fusion models to fuse electronic nose and surface acoustic wave sensor data for apple defect detection. *Sensors and Actuators B: Chemical*, 125(1):301–310, 2007.

Eduard Llobet, Evor L Hines, Julian W Gardner, and Stefano Franco. Non-destructive banana ripeness determination using a neural network-based electronic nose. *Measurement Science and Technology*, 10(6):538, 1999.

Murugesapandian Paulraj, Chengalvarayan Radhakrishnamurthy Hema, Krishnan R Pranesh, and Mohd Radzi Siti Sofiah. Color recognition algorithm using a neural network model in determining the ripeness of a banana. In *Proceedings of the International Conference on Man-Machine Systems (ICoMMS)*. Universiti Malaysia Perlis, 2009.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

Hasnida Saad, Ahmad Puad Ismail, Norazila Othman, Mohamad Huzaimy Jusoh, Nani Fadzlina Naim, and Nur Azam Ahmad. Recognizing the ripeness of bananas using artificial neural network based on histogram approach. In *Signal and Image Processing Applications (ICSIPA)*, pages 536–541. IEEE, 2009.