Food Image Recognition by Using Convolutional Neural Networks (CNNs)\(^1\)

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Abstract. Food image recognition is one of the promising applications of visual object recognition in computer vision. In this study, a small-scale dataset consisting of 5822 images of ten categories and a five-layer CNN was constructed to recognize these images. The bag-of-features (BoF) model coupled with support vector machine was first tested as comparison, resulting in an overall accuracy of 56%; while the CNN performed much better with an overall accuracy of 74%. Data expansion techniques were applied to increase the size of training images, which achieved a significantly improved accuracy of more than 90% and prevent the overfitting issue that occurred to the CNN without using data expansion. Further improvement is within reach by collecting more images and optimizing the network architecture and relevant hyper-parameters.

Keywords: food recognition; convolutional neural network; data expansion

1. INTRODUCTION

Due to the widespread use of low-cost imaging devices like smartphone cameras, more and more applications are being developed in computer vision to facilitate automatic object recognition, among which food image recognition has recently gained much attention [1-4]. Nowadays, people, especially diabetes patients, are increasingly cautious about their diet for improved health care. Food image recognition provides a simple means to estimate the dietary caloric intake and evaluate people’s eating habits, by using cameras to keep track of their food consumption.

In recent years, Convolutional neural networks (CNN) have enjoyed great popularity as a means for image classification/categorization since Krizhevsky et al [5] won the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) 2012 competition. CNN, as a variant of the standard deep neural network (DNN), is characterized by a special network architecture consisting of alternating convolutional and pooling layers [6], to extract and combine local features from a two-dimensional input. Compared to conventional hand-crafted feature extraction based approaches, CNN is advantageous since it is able to learn optimal features from images adaptively. In implementing CNN for image classification, researchers have to collect such a large-scale dataset as the ILSVERC that contains more than one million images [5, 7], for network training because of the need for learning a large number of parameters involved in the network, which, however, is not a trivial task. One simple way to deal with the situation is to apply the CNN model that has been pre-trained based on a large-scale image data [1, 8], which is so-called transfer learning. Another way one can choose is to algorithmically expand the existing training data, e.g., by performing affine transformations to the raw images.

This study was aimed to apply CNNs aided with data expansion techniques to a ten-class small-scale food image data. As comparison, a conventional a bag-of-feature (BoF) model combined with linear support vector machine (SVM) based approach was also employed for food image recognition. Experimental results demonstrated the superior performance of CNN and the effectiveness of data expansion techniques in training small-scale data.

2. EXPERIMENTATION

2.1. Database

\(^1\) This study was part of the CSE803 final project
5822 color images, representing ten-class food, were collected from the ImageNet (http://image-net.org/). The number of images for each category is summarized in Table 1.

| Category   | Image Number |
|------------|--------------|
| Apple      | 1050         |
| Banana     | 310          |
| Broccoli   | 327          |
| Burger     | 519          |
| Egg        | 626          |
| Frenchfry  | 296          |
| Hotdog     | 639          |
| Pizza      | 1248         |
| Rice       | 352          |
| Strawberry | 455          |

These images had a large variations in quality and size. Some of them have a neat, uniform background while some have clutered background. Prior to image analysis, all the images were down-sampled to a fixed resolution of 128x128, and then randomly divided into two parts for training and test with a 4:1 ratio, resulting in 4654 training and 1168 test images.

2.2. BoF

The BoF model has been extensively used for image classification. In this method, an image is treated as a collection of orderless descriptors extracted from local patches, which are quantized into discrete visual words and represented by a compact histogram [9]. Scale invariant feature transform (SIFT) descriptors that are not affected by perspective, scale, occlusion or illumination [10], are one of the most robust and popular feature descriptors. In this study, the BoF model with SIFT descriptors was used to extract features that were then fed to linear SVM for image classification, and this approach was implemented by means of the VLFeat library [11].

2.3. CNN

The architecture of the CNN used in this study is schematically illustrated in Fig. 1. The network has four layers of hidden neurons (three convolutional-pooling and one fully-connected), apart from a final layer of output neurons (the input is not considered as a layer). The input contains 128x128x3 neurons, representing the RGB values for a 128x128x3 image. The first convolutional-pooling layer uses a local receptive field (also known as convolutional kernel) of size 7x7 with a stride length of 1 pixel to extract 32 feature maps, followed by a max pooling operation conducted in a 2x2 region; the second and third convolutional-pooling layers use 5x5 and 3x3 local receptive fields, resulting in 64 and 128 feature maps, respectively, and the other parameters remain unchanged. The fourth layer is a fully-connected layer with 128 rectified linear units (ReLU) neurons, and the output layer has 10 softmax neurons that correspond to the ten categories of food. The three convolutional-pooling layers also use ReLU activation functions.

![Fig. 1. Schematic of the architecture of convolutional neural networks](image)

The network was trained with the stochastic gradient descent (SGD) algorithm with a cross-entropy cost function. The dropout that randomly eliminate a portion of neurons from the network was used to reduce possible overfitting. The dropout rates of 0.25 and 0.5 were set for the third convolutional-pooling layer and the fully-connected layer, respectively. Training a DNN requires to select a set of hyperparameters, among which the learning rate ($\eta$) is the the most critical one affecting the training performance. A fixed learning rate over the entire training process seems suboptimal, since it does takes account of the dynamical training behavior. Here, a dynamically updated learning rate was used, which was an exponential
function of cost $\eta = \eta_0 \exp(C)$ where $\eta_0$ is set to 0.001 through trials and errors and $C$ is the training loss. Such learning rate updating schedule is directly related to the training performance. At the initial stage, the training loss was large, resulting in a large learning rate to speed up the training process; gradually, the learning rate decreased with the loss, which helped avoid overshooting the best result.

Given the limited images available, affine transformations including rotation, translation and scaling were conducted to expand the training data. Upper bounds were set up in performing these transformations, within which each image was randomly subjected to those transformations, which substantially increased the data size. Fig. 2 shows an example of a raw image and expanded images.

![Fig. 2. The raw image (right) and expanded images (left)](image)

The CNN was implemented by using the keras package on top of theano in the Spyder environment (the detail implementation can be found at: https://github.com/jingweimo/food-image-classification-), which was configured to use GPU for training.

3. RESULTS AND DISCUSSION

The BoF combined with SVM resulted in an overall accuracies (the ratio of the number correctly recognized images to the number of total images) of 68% and 56% for training and test images, respectively. Table 2 presents the confusion matrix on the test images and recognition rates (i.e., the average of true positive and true negative rates) for all the categories.

|                | Apple | Banana | Broccoli | Burger | Egg | Frenchfry | Hotdog | Pizza | Rice | Strawberry |
|----------------|-------|--------|-----------|--------|-----|------------|--------|-------|-----|------------|
| Apple          | 178   | 1      | 0         | 4      | 8   | 0          | 2      | 6     | 5   | 7          |
| Banana         | 2     | 43     | 1         | 2      | 4   | 4          | 5      | 2     | 1   | 1          |
| Broccoli       | 1     | 0      | 28        | 2      | 0   | 3          | 2      | 24    | 1   | 4          |
| Burger         | 5     | 0      | 2         | 72     | 2   | 2          | 7      | 12    | 1   | 1          |
| Egg            | 20    | 1      | 2         | 7      | 75  | 1          | 6      | 6     | 6   | 1          |
| Frenchfry      | 1     | 4      | 3         | 4      | 1   | 21         | 6      | 16    | 1   | 0          |
| Hotdog         | 5     | 8      | 4         | 10     | 4   | 9          | 76     | 10    | 2   | 1          |
| Pizza          | 5     | 0      | 4         | 5      | 1   | 1          | 7      | 221   | 3   | 4          |
| Rice           | 6     | 1      | 1         | 2      | 4   | 1          | 1      | 18    | 35  | 1          |
| Strawberry     | 11    | 1      | 2         | 1      | 1   | 0          | 1      | 29    | 1   | 45         |
| R.R.           | 0.89  | 0.82   | 0.71      | 0.83   | 0.79| 0.67       | 0.78   | 0.87  | 0.74| 0.73       |

Note: R.R. denotes the recognition rate that is calculated as the average of the true positive and true negative rates.

Apple and pizza gave the two highest recognition rates, which were mainly because the two categories had a large number of training images; while french-fry and broccoli was the two hardest categories, the
majority of which were misclassified into another distinct class. The BoF based approach did not perform well as expected, which was possibly because that the extraction of SIFT descriptors was conducted only to grayscale images, and also the parameter optimization was not fully done in descriptor quantization.

The CNN was first implemented without using data expansion techniques. Fig.3 show the accuracy and loss curves during training with the maximum training epoch set to 100. A large gap between training and test occurred after 10 epochs, indicating the presence of overfitting. The highest accuracy on the test images was found to be 74%, corresponding to a training accuracy 95%. These results were much better than those obtained by the BoF approach, which confirmed the superiority of CNN.

![Fig. 3. Accuracy (left) and loss (right) curves. The training process was early stopped since no improvement in test accuracy for a long time of period.](image)

Then, the CNN was trained with the expanded image data. As illustrated in Fig. 4, two significant improvements were achieve through almost trivial data transformations. First, the test accuracy was greatly elevated to a level up to 87% within 100 epochs, and second, the overfitting issue observed above was completely eliminated. The data expansion substantially increases the effective size of the training data, thus helping improve the training performance and making the model generalize well.

![Fig. 4. Accuracy (left) and loss (right) curves.](image)

From the accuracy and loss curves, it seemed that the CNN model could be further improved by increasing the training epochs. So, another three training schemes with 200, 400 and 600 epochs were implemented. Fig. 5 shows their accuracy and loss curves. The test accuracy did increase further, but not by a large margin. After 200 epochs the training accuracy started to exceed the test accuracy and the gaps between training and test were likely to enlarge. Training the CNN with 400 epochs resulted in the highest test accuracy of more than 90%; while training 600 epochs increased the training accuracy but not the test.
accuracy which seemed to level off around 90%. A slight overfitting issue was possible to escalate, and one could not keep increasing the test accuracy by simply increasing the training epochs. Data expansion is an effective method for improving the CNN performance, but it does not overshadow the importance of manually collecting more training data.

![Graphs showing model accuracy and loss with training epochs set to 200, 400, and 600 (from top to bottom)].

**Fig. 5.** Accuracy (left) and loss (right) curves with training epochs set to 200, 400, and 600 (from top to bottom), where early stopping could occur due to no accuracy improvement on test images. The training process would be early stopped when no improvement in test accuracy for a long time of period.

Table 3 presents the confusion matrix by the best CNN model for the test images and the corresponding recognition rates for each food category. Compared with Table 2, the CNN model resulted in the overall accuracy improved from 56% to 90%, and the average recognition rate from 0.78 to 94%.
Table 3 Confusion matrix and recognition rates by CNN on the test images

|       | Apple | Banana | Broccoli | Burger | Egg | Frenchfry | Hotdog | Pizza | Rice | Strawberry |
|-------|-------|--------|----------|--------|-----|-----------|--------|-------|------|------------|
| Apple | 193   | 6      | 1        | 0      | 1   | 0         | 2      | 1     | 0    | 6          |
| Banana| 4     | 49     | 0        | 0      | 4   | 2         | 3      | 0     | 0    | 0          |
| Broccoli| 0   | 0      | 64       | 0      | 0   | 0         | 1      | 1     | 0    | 0          |
| Burger| 1     | 0      | 0        | 87     | 0   | 1         | 9      | 6     | 0    | 0          |
| Egg   | 3     | 1      | 0        | 2      | 110 | 2         | 5      | 1     | 2    | 0          |
| Frenchfry| 0  | 2      | 0        | 0      | 0   | 53        | 1      | 4     | 0    | 0          |
| Hotdog| 1     | 2      | 0        | 5      | 0   | 3         | 109    | 8     | 0    | 0          |
| Pizza | 0     | 0      | 0        | 3      | 0   | 1         | 6      | 239   | 0    | 1          |
| Rice  | 0     | 0      | 0        | 1      | 0   | 0         | 1      | 5     | 64   | 0          |
| Strawberry| 3  | 0      | 0        | 0      | 0   | 0         | 0      | 0     | 0    | 88         |
| R.R.  | 0.95  | 0.89   | 0.98     | 0.91   | 0.93| 0.94      | 0.91   | 0.96  | 0.95 | 0.98       |

Note: R.R. denotes the recognition rate that is calculated as the average of the true positive and true negative rates.

4. CONCLUSIONS

This study reported on the applications of CNNs to a ten-class small-scale food image data. A five-layer CNN model was constructed achieved the best test accuracy of 74%, which was better than the accuracy of 56% achieved by the BoF approach. The CNN model suffered from noticeable overfitting due to limited training data. This issue was well addressed by expanding the training data through affine transformations, which also considerably increased the overall test accuracy to a level of over 90%. Training the CNNs with different epochs showed the limited room for further improvement in test accuracy data expansion, which could be achieved by collecting more training data or by optimizing the architecture and hyper-parameters of the network, rather than by increasing the training epochs in the current framework, which, otherwise, would aggravate the overtraining problem.

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