Deep Convolutional Network for Handwritten Chinese Character Recognition

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Abstract

In this project we explored the performance of deep convolutional neural network on recognizing handwritten Chinese characters. We ran experiments on a 200-class and a 3755-class dataset using convolutional networks with different depth and filter numbers. Experimental results show that deeper network with larger filter numbers give better test accuracy. We also provide a visualization of the learned network on the handwritten Chinese characters.

1. Introduction

Deep convolutional neural network (CNN) has become the architecture of choice for complex vision recognition problems for several years. There has been a lot of research on using deep CNN to recognize handwritten digits, English alphabets, or the more general Latin alphabets. Experiments have shown that well-constructed deep CNNs are powerful tools to tackle these challenges. As the recognition of characters in various languages has attracted much attention in the research community, a natural question is: How does deep CNN perform for recognizing more complex handwritten characters? In this project, we will explore the power of deep CNN on the classification of handwritten Chinese characters.

Compared to the task of recognizing handwritten digits and English alphabets, the recognition of handwritten Chinese characters is a more challenging task due to various reasons. Firstly, there are much more categories for Chinese characters than for digits and English characters. As a comparison, there are 10 digits for usual digit recognition tasks, and there are 26 alphabets for English, while there are in total over 50,000 Chinese characters and around 3,000 of them are for everyday use. Secondly, most Chinese characters have much more complicated structures and consist of much more strokes compared to digits or English characters. Figure 1 shows a comparison of different handwritten characters. Thirdly, handwriting style for Chinese characters varies hugely from person to person. Moreover, the existence of joined-up handwriting makes the recognition even more difficult. For example, Figure 2 shows the influence of different handwriting styles on the appearance of handwritten Chinese characters. It is even a challenging task for a well-educated Chinese to recognize all the handwritten characters correctly.

In this project, we will focus on two specific questions: 1) How will the architecture and depth influence the accuracy of CNN on recognizing handwritten Chinese characters? 2) Does the extracted features make sense in terms of visualization? The rest of the report is organized as follows. We will first introduced the dataset and our network configurations in Section 2 and Section 3. Then we will introduce how we implement and train our networks in Section 4. Afterwards we present our experimental results in Section 5 and analyze the results in Section 6. Finally, we will discuss the related work in Section 7.

(a) Digit (b) English (c) Chinese

Figure 1: Example of handwritten characters

2. Data

2.1. Dataset

For this project we use the CASIA offline database, as described in [6]. The data consists of plain gray-scale images of isolated handwritten Chinese characters, as shown in Figure 2. Specifically, we will use the *HWDB1.1* dataset, which totally includes 3,755 Chinese characters and 171 alphanumeric and symbols. As is presented in Table 1, each category contains handwritten images from approximately 300 writers (with minor difference for some categories), and each writer contributes one image to each category. As released, the full dataset is split into two parts: a training set

Figure 2: Different data examples in the same category. Examples on each row come from different writers and correspond to the same Chinese character: 艾, 斌, and 棉 respectively. Very different handwriting styles across writers could be observed.

Dataset	# Writers	# Classes	# Total Samples	# Chinese characters	# Symbols
CASIA HWDB1.1	300	3,755	1,172,907	1,121,749	51,158

Table 1: HWDB1.1 Dataset Information

and test set. Test set contains 60 randomly sampled images for each category, and training set contains the rest (approximately 240). In this project, for debugging and comparing different models during training, we further split the original training set into two parts: a training set and a validation set, with training set containing 200 images for each category and validation set contains the rest (approximately 40).

Training on the full dataset (over 1 million examples) can take many hours or days even with the fastest GPU. Constraint by the computation resources we have access to, we ran our major experiments (for model comparison and visualization) on a subset of the full dataset, which contains 200 randomly sampled classes. The size of training set, validation set and test set for each class remains unchanged.

We also ran experiments on the full dataset to evaluate the power of our best models. This full dataset contains all the 3,755 classes. It is worth noting that there are much more classes than examples for each classes in the training set. The information about two datasets are listed in Table 2.

2.2. Preprocessing

The released dataset contains examples in binary format, along with labels. So the first step of the data processing is to convert the binary data into image format. Here we use *.jpg* to encode the image and store the image files. The converted images have background labeled as 255 and foreground pixels in 255 gray levels (0-254).

As it is used in [2], here we followed a three-step preprocessing approach: resizing, contrast maximization and image mean subtraction. Given a raw input image describing a handwritten Chinese character, we first resized the image into a normalized size. After visual inspection of several examples, we found 56×56 to be a proper size. The resizing was done uniformly, and the biggest dimension of each character determined the resizing factor. We also added 4-pixel white margins to the resized image, and centered the character in the final resized image. Thus, a final resized image has a size of 64×64. Secondly, we rescaled the image values to maximize the contrast. In another word, we forced the image to have values ranging from 0 to 255. Finally, we computed the mean image with all images from the training set, and subtracted the mean image from each example before we fed the example into the following models. A comparison of images after each step is shown in Figure 3.

3. Network Configurations

To explore the performance of deep convolutional neural networks on classifying handwritten Chinese characters, and answer the questions proposed in Section 1, we implemented a few experiments with different sets of convolutional network configurations. Specifically, we evaluated the performance of CNN on the task of 200-class classification, 3755-class classification, transfer learning from full dataset to 200-class dataset, and a visualization of the learned network. Now we presented network configurations for each of the experiment and the reasons of our design choices in the following subsections.

Dataset	# Classes	Training (per class)	Validation (per class)	Test (per class)	# Total examples
Subset	200	200	40	60	59,711
Full	3,755	200	40	60	1,121,749

Table 2: Training set, validation set and test set information for the subset and full dataset

Figure 3: An example image (corresponding to the Chinese character "爱") after each of the three steps. From left to right: raw input image, resized image, and rescaled image (contrast maximized). Note that black borders are added to the images to show the sizes. The final output with image mean subtracted is not included in this figure.

3.1. 200-class classification

We first ran experiments on the 200-class dataset with the objective to compare the influence of different CNN architectures on the final classification accuracy for handwritten Chinese characters. Note that experiments on the full dataset can give more precise and compelling results, but running the experiments on the full dataset requires much larger GPU computation power (1121749 examples vs. 59711 examples) to complete in acceptable time. As this is a class project, we have very limited GPU computation power, and have to share it across many groups of students, we instead implemented our major experiments on the 200-class dataset. Since we randomly sampled the dataset from the full dataset, we assume that the results on the 200-class dataset is representative enough to draw solid conclusions. We would like to note the readers that experiments on a larger dataset could be done in the future to validate our findings.

During the design of the experiments, we keep the following questions in our mind:

1. How does the depth of the network influence the classification accuracy?
2. How does the number of filters in the convlutional layers influence the classification accuracy?
3. Does adding a convolutional layer help more or adding a fully-connected layer help more in terms of the test accuracy?

To explore these questions, following a similar approach introduced in the VGGNet paper [7], we designed and implemented 8 convolutional neural network architectures, as it is shown in Table 3. These layers are named by the number of weight layers (convolutional layers and fully-connected layers). For example, model M5 has three convolutional layers and two fully-connected layers. Minor variants of the architecture are also reflected in the name of the network, e.g. M6- and M6+.

To explore the influence of depth on the classification accuracy, we started by implementing a 5-layer network, i.e. M5, and then added layer to this network step by step. We finally pushed the depth of our model to 11 layers, i.e. M11. The design choices are made based on several reasons: A convolutional network with fewer layers than M5 is not expressive enough to achieve a very high accuracy on the handwritten Chinese character recognition task, while a convolutional network with more than 11 layers can give us very limited extra performance, and requires significantly larger effort to train. This insight is proved by our experiment results presented in later section. While the depth of our networks are increased from left to right as shown in Table 3, we fixed the filter size of all the filters to 3. In order to keep the size of the output, we consequently fixed the stride size to 1 pixel and the zero padding size to 1 pixel. The choice of uniform small filter sizes significantly reduces the number of parameters in the network and makes the networks easier to train, while still keeps the expressive power of the models. This is the same approach used in the VGGNet paper [7], and a more detailed discussion and comparison of filter sizes is shown in that paper.

To investigate the influence of the number of filters in the network, specifically in the convolutional layers, on the classification accuracy, we designed two variants for our 6-layer model M6, i.e. M6- and M6+. Model M6- halves the number of filters used in all the convolutional layers com-

<table>
<tr><td colspan="8">CNN Configurations</td></tr>
<tr><td>M5</td><td>M6-</td><td>M6</td><td>M6+</td><td>M7-1</td><td>M7-2</td><td>M9</td><td>M11</td></tr>
<tr><td>5 weight layers</td><td>6 weight layers</td><td>6 weight layers</td><td>6 weight layers</td><td>7 weight layers</td><td>7 weight layers</td><td>9 weight layers</td><td>11 weight layers</td></tr>
<tr><td colspan="8"></td></tr>
<tr><td colspan="8">input data (64 x 64 gray-scale image)</td></tr>
<tr><td>conv3-64</td><td>conv3-32</td><td>conv3-64</td><td>conv3-80</td><td>conv3-64</td><td>conv3-64</td><td>conv3-64</td><td>conv3-64
conv3-64</td></tr>
<tr><td colspan="8">maxpool</td></tr>
<tr><td>conv3-128</td><td>conv3-64</td><td>conv3-128</td><td>conv3-160</td><td>conv3-128</td><td>conv3-128</td><td>conv3-128</td><td>conv3-128
conv3-128</td></tr>
<tr><td colspan="8">maxpool</td></tr>
<tr><td>conv3-256</td><td>conv3-128</td><td>conv3-256</td><td>conv3-320</td><td>conv3-256</td><td>conv3-256</td><td>conv3-256
conv3-256</td><td>conv3-256
conv3-256</td></tr>
<tr><td colspan="8">maxpool</td></tr>
<tr><td rowspan="2"></td><td>conv3-256</td><td>conv3-512</td><td>conv3-640</td><td>conv3-512
conv3-512</td><td>conv3-512</td><td>conv3-512
conv3-512</td><td>conv3-512
conv3-512</td></tr>
<tr><td colspan="6">maxpool</td></tr>
<tr><td colspan="5"></td><td colspan="3">FC-1024</td></tr>
<tr><td colspan="8">FC-1024</td></tr>
<tr><td colspan="8">FC-200 / FC-3755</td></tr>
<tr><td colspan="8">softmax</td></tr>
</table>

Table 3: CNN configurations

pared to M6. M6+ increases the number of filters used in the first convolutionial layer from 64 to 80, and doubles the filter number in each subsequent convolutional layer. We did not double the filter number from M6 to M6+ due to the constraint of our GPU architecture: Doubling the filter number will cause the intermediate matrices to be overlarge, and our GPU does not allow this. All other aspects of the network remain unchanged for M6- and M6+.

The third question is explored by our design of the two variants of 7-layer networks, i.e. M7-1 and M7-2. For M7-1, we added an extra convolutional layer right before fully-connected layers compared to M6, and for M7-2, we added a fully connected layers before the fully-connected layer in M6. We expect the comparison of the results for M7-1 and M7-2 provide us clues to answer the third question. For model M9 and M11, we built them on top of 7-layer networks and used three fully-connected layers for both. The difference exists in the number of convolutional layers: M9 used 6 convolutional layers, and M11 used 8 convolutional layers.

During training, the inputs to our network are 64×64 gray-scale images, as discussed in previous section. Spatial pooling is carried out by max-pooling layers denoted by "maxpool" in the table. All the max-pooling is carried out over a 2×2 pixel window, with stride of 2 pixel. Please note that we used slightly different number of max-pooling layers in the networks: Since the M5 model only includes 3 convolutional layers, we thus only use three max-pooling layers for it; for all the subsequent models, we use four max-pooling layers, and if the layer contains more than four convolutional layers, we stacked two convolutional layers before fed the output to a max-pooling layer, as shown in the table.

All the hidden layers (convolutional layers and intermediate fully-connected layers) are followed by rectification non-linearity (ReLU layer), which is not shown in Table 3. We did not include Local Response Normalisation (LRN) layers in our network. The inclusion of ReLU layers and exclusion of LRN layers are explained at large in previous research [7], and we do not provide details here. The output of the last fully-connected layers are fed into a softmax layer to compute the probabilities.

3.2. 3755-class classification

To evaluate our model not only on the subset of data, but also on the full dataset, we also ran the 3755-class classification task. Constraint by time and computation power, we only implemented four models for this task, i.e. M6, M6+, M7-1, M7-2. The only difference is that we use 3755 neurons for the last fully-connected layer for each model instead of 200 neurons. We did not include M5 and M6- models based on our experience on the 200-class classification experiments that M5 and M6- are less expressive compared to larger models. And M9 and M11 are less easier to train

over more than 1 million examples, and the learned model provides us with very limited accuracy gain on the 200-class classification, thus we did not include them in this part, either.

All the other aspects of the networks remain the same for the 3755-class classification task.

3.3. Visualization

Visualization is a natural way to learn about a neural network and understand how a specific network succeeds or fails at classifying an example. For convolutinal neural network, visualizing the filters at convolutional layers and data output after each layer is intuitive and helpful. Thus, we focused on visualizing the filters and data output in the network for this part of experiments.

In order to maximize the visual effect of the result and make the visualization more intuitive, we did not restrict our filter size to 3 in this part. Instead, we experimented with different architectures with different filter sizes, and set our final architecture to what is shown in Figure 4. This network consists of four convolutional layers and two fully-connected layers. We used filter size of 11, 7, 5 and 3 for the four convolutional layer respectively, as a larger filter can present more details after visualized. The data output size and parameter size of each layer is also shown in the figure for reference.

4. Classification Settings

In the previous section we introduce the architecture of our convolutional networks for different experiments. In this section, we present the classification settings in terms of implementation of the networks, training and testing settings.

4.1. Implementation

All the convolutional neural networks that we introduced are implemented in Caffe [1]. Specifically, we used the Caffe command line interface for model training and testing, and we used the Caffe python interface for model ensemble and visualization. We implemented the first two preprocessing steps in MATLAB and the image mean subtraction is implemented in Caffe. Both the training and testing of all the models were run on the Stanford Farmshare machines, and specifically we used *Rye* machines to exploit the GPU power. The *Rye* machine contains 6 Tesla C2070 GPU, each with a memory size of around 5GB. This memory size is very limited for many modern deep learning tasks, and restricted the design of our models.

4.2. Training

We used similar convolutional neural network training procedures with [7]. Namely, the training is carried our by optimizing the softmax objective using mini-batch gradient descent with momentum. The batch size is set to 100 due to the limitation of GPU architecture. The momentum is set to 0.9 for all networks. The training is regularized by weight-decay (L2 regularization) and dropout at each fully-connected layer. We set the weight-decay to 0.0005 and dropout rate to 0.5 for all the networks.

The evaluation during training is carried over the validation set, and we evaluated each model after 0.5 epoch. The initial learning rate is set to 0.01 and we halved the learning rate after every 3 epochs. Model M5 through M7-2 are trained for 15 epochs, and the learning rate was halved for 5 times in total. For deeper networks, i.e. M9 and M11, we trained them for 18 epochs and the learning rate was halved for 6 times as they requires more time to train.

The initialization of certain networks is a little bit tricky. For model M5 through M7-2, initializing the weights by sampling from normal distribution with zero mean and a variance of 0.01 and initializing the biases with 0s is enough. However, for deeper networks M9 and M11, initializing the weights randomly will result in a network that learns very slowly or does not learn at all. Thus, we instead initialized the M9 and M11 with the trained 7-layer network and fine-tuned over the learned weights. This trick makes the training process for M9 and M11 converge within 18 epochs.

Since the input to the networks is gray-scale handwritten Chinese characters already centered in the image, we did not use data augmentation such as random cropping, scaling or shifting. Thus, the influence of data augmentation on the handwritten Chinese character recognition task remains undiscussed.

4.3. Testing

Testing is carried over the test set and is also implemented in Caffe command line interface (with exception to model ensemble). For each designed model, we tested for two accuracies: top-1 accuracy and top-5 accuracy, with top-5 accuracy representing the accuracy that the correct label presents in the top 5 predicted labels. In addition to the designed models from M5 through M11, we also tested the result of model ensembles. Model ensemble is implemented in Caffe python interface and averages the predicted probabilities generated by several different models to make a final prediction over an example.

5. Experimental Results

Experiments were run following the network architectures and classification settings introduced in previous sections. In this section we report the experimental results.

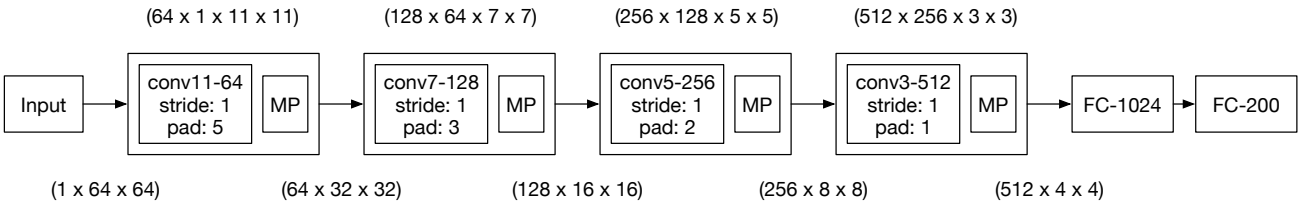


Figure 4: Architecture of the network for visualization. The data output size of each layer is shown at the bottom, and the paramter size of each layer is shown on the top.

Model	Validation Accuracy (%)	Test Accuracy (%)	
		Top 1	Top 5
M5	95.9	95.7	99.1
M6-	96.8	96.6	99.5
M6	97.0	96.9	99.5
M6+	97.4	97.0	99.6
M7-1	97.3	97.1	99.6
M7-2	97.0	96.8	99.6
M9	97.4	97.2	99.6
M11	**97.7**	97.3	99.6
Ensemble	N/A	**98.1**	**99.7**

Table 4: Classification results on the 200-class dataset

5.1. Classification results

The classification results for the 200-class dataset is reported in Table 4. Here we also included the results for model ensemble. The model ensemble makes predictions by averaging the results from M6, M6+, M7-1, M7-2, M9 and M11. We did not include M5 and M6- in the model ensemble because they gave relatively low validation accuracy compared to other models. The best test accuracies are achieved by model ensemble.

The classification results for the 3755-class dataset is reported in Table 5. We also included the results for model ensemble. It makes predictions by averaging the results from all single models (M6, M6+, M7-1, M7-2). Again, the best test accuracies are achieved by model ensemble.

5.2. Network visualization

The visualizations of the filters and data outputs in network described in previous section are shown in Figure 5 and Figure 6. We used an example of Chinese character "祝" to demonstrate the visualization. Restricted by space limitations, for conv2, conv3 and conv4, we only presented visualizations for the first 100 filters. In addition, the visualization of conv4 output is visually filled with black boxes, thus we instead visualize the pool4 output.

6. Discussion

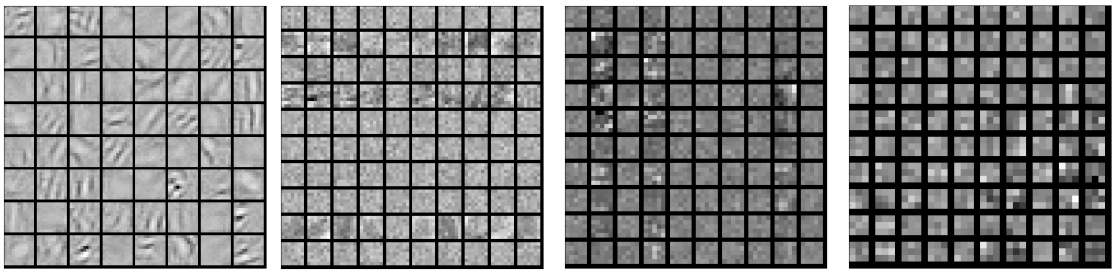
As it is shown in Table 4, the best test accuracy is achieved by model ensemble on the 200-class classification task. If we examine the models with the same filter size but different depth (i.e. M5, M6, M7-1, M9, and M11), we could find that the test accuracy increases as the depth of the CNN increases. This is an interesting observation and it aligns with the conclusion from the VGGNet paper [7]. If we further examine the results achieved by different models, we can easily find that the accuracy gain that a deeper network can give us on top of a shallower network is shrinking as the depth increases. For instance, the test accuracy gain from M5 to M6 is 0.9%, the accuracy gain from M6 to M7-1 is 0.2%, and the accuracy gain from M7-1 to M9 and M9 to M11 is 0.1%. In another word, the accuracy gain that the increased depth of the network can provide us with follows the law of "diminishing returns".

If we compare the results for all the 6-layer networks, i.e. M6-, M6 and M6+, it is easily found that larger filter number in the convolutional layer can provide us with larger test accuracy (M6-:96.6% < M6:96.9% < M6+:97.0%). Though the difference is quite intuitive and obvious, since we only ran the comparison experiments for 6-layer networks, the generalization of this observation still needs to be proven by more experiments.

If we compare the results for M7-1 and M7-2, we could easily observe that when we have a relatively small num-

Model	Validation Accuracy (%)	Test Accuracy (%)	
		Top 1	Top 5
M6	94.9	94.6	98.9
M6+	95.1	94.9	99.1
M7-1	**95.5**	95.1	99.2
M7-2	95.3	95.0	99.2
Ensemble	N/A	**95.5**	**99.3**

Table 5: Classification results on the 3755-class dataset



(a) conv1 (b) conv2 (c) conv3 (d) conv4

Figure 5: Visualization of network filters

ber of convolutional layers (4 in this case), adding an extra convolutional layer can provide us with larger performance gain compared to adding an extra fully-connected layer. In fact, if we compare the result of M7-2 to that of M6+, we can also observe that the benefit of increasing filter number beats that of adding extra fully-connected layer. Note that this conclusion is interesting but less generalizable since we only ran our experiments on 7-layer networks.

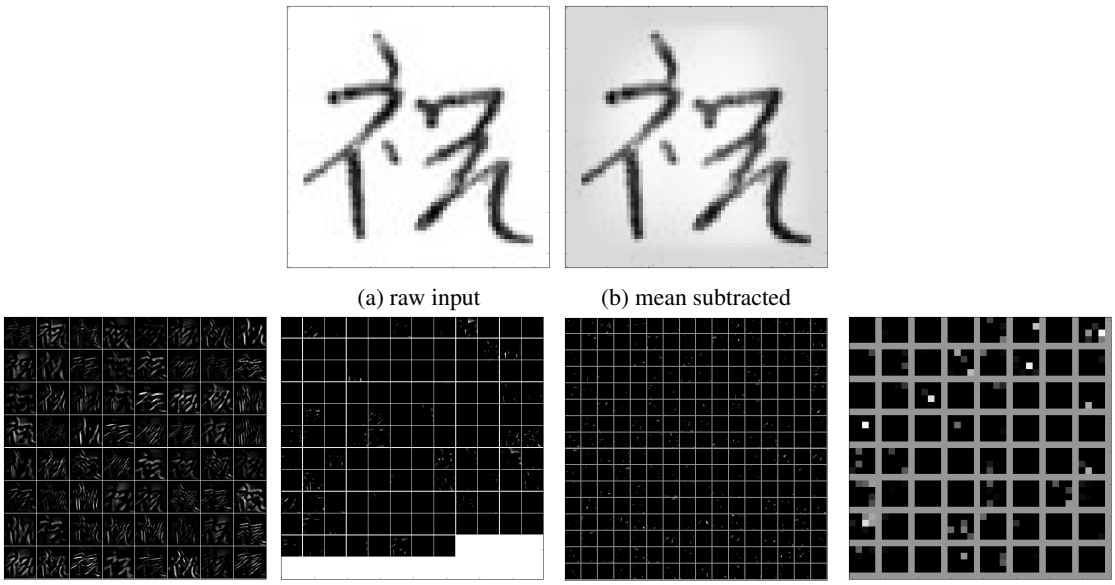
For the 3755-class classification task, as shown in Figure 5, the best validation accuracy is achieved by model M7-1 and the best test accuracy is again achieved by model ensemble. The test accuracy of classifying over 3755 classes is significant lower than that over 200 classes, but is still very impressive, with an accuracy of 95.5%. This result is possible to beat a human classifier after a Chinese reader manually examined the test examples, but no experiment can show this strictly. The top-5 accuracies are very high for both cases. Adding layers, while helps increase the top-1 accuracy, contributes little to the top-5 accuracy, since the top-5 accuracy is already very high.

The visualization of the network filters and outputs is very intuitive. The filter of the first convolutional layers presents the appearance of small natural strokes. The filters of later convolutional layers demonstrates patterns of the characters on larger scales. This observation aligns very well with our intuitions.

7. Related Work

Our work on exploring the performance of deep convolutional neural network on handwritten Chinese character recognition is inspired by a few related works. LeNet [5] is the earliest work of applying convolutional neural network to recognizing characters with noise. It demonstrated that convolutional neural network system can achieve high accuracy on vosual recognition of zip codes (digits) symbols and English alphabets. However, the networks that are used in the paper is relatively shallow and no results on handwritten Chinese character recognition is reported in the paper. Krizhevsky et al.'s work [4] on using convolutional neural network (AlexNet) to tackle the ImageNet challenge caught a lot of attention by increasing the depth of the network and implementing many tricks to optimize the performance of the convolutional network. Their work demonstrated the potential of using deep convolutional network to solve complex image recognition problems. Later, VGGNet [7] further pushed the depth of the convolutional neural networks to 13 layers and shows that the deeper the network, the better the performance can be achieved on complex visual recognition problems. It also proposed the preference of small filter size (3) to larger filter sizes for deeper neural networks.

In 2011, Chinese Academy of Science released the CASIA dataset [6] of online and offline isolated handwritten Chinese character images. Later, some attempts [2] [3] have been made to explore the power of convolutional neural network on recognizing Chinese handwritten characters. In



(a) raw input (b) mean subtracted

(c) conv1 output (d) conv2 output (e) conv3 output (f) pool4 output

Figure 6: Visualization of layer outputs

one project, researchers explored the possibility of transfer learning from Latin characters to Chinese characters. In another piece of work, a multi-column neural network proposed in [**?**] is used to synthesize the predictions of several different CNN architectures and make final predictions. This idea is the origin of model ensembles. This work shows that well-trained CNN can achieve high performance on recognizing handwritten Chinese characters, especially when CNNs are combined to form model ensemble. However, the CNN used in this work is relatively shallow, and no discussion about the influence of architectural factors of CNN on the final result is made in this paper. Moreover, no visualization of the learned networks is presented.

8. Conclusion

In this project we explored the problem of recognizing handwritten Chinese characters. Specifically we use deep convolutional neural networks and achieved very impressive performance. We ran experiments on a 200-class and a 3755-class dataset using convolutional networks with different depth and filter numbers. Our main findings are that for convolutional neural network with small filter sizes: 1) the deeper the network, the larger the accuracy; 2) increasing the depth gives us diminishing returns in terms of accuracy but highly increases the difficulty of training; 3) increasing the filter number in a moderate range can increase the accuracy; 4) for networks with relatively few convolutional layers, the benefit of adding extra convolutional layer beats that of adding extra fully-connected layer. We also find that using model ensemble of networks with similar accuracies beats all single networks. Our visualization of the learned network on the handwritten Chinese characters is very intuitive.

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