PR Final Project Report

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Methodology:

First of all, in this final project, the first thing to consider is which network architecture to use for training the data. I have chosen ResNet34. ResNet series is widely used in deep learning and has shown excellent results in various tasks. I only tried ResNet34 due to limited time and computational resources, which prevented me from trying out the entire ResNet series.

The next challenge to address is the classification method and loss calculation. The standard ResNet architecture combined with CrossEntropyLoss can only deal with a single label. However, for Task 2 and Task 3, we need to handle the recognition of multiple characters. My solution is to create a separate model for each task. For Task 2, which involves recognizing two characters, I use two fully connected branches to output the results separately. Branch 1 focuses on recognizing the first character, while Branch 2 focuses on recognizing the second character. I calculate the CrossEntropyLoss for each branch and then combine them to obtain the total loss. This approach allows us to simultaneously address the challenges of multilabel classification and character recognition order. The same approach is applied for Task 3, which involves recognizing four characters.

Furthermore, I found that the data provided for these three tasks was severely insufficient. To improve performance, it was necessary to increase the amount of training data. After trying out several packages, I opted for two Python packages: Augmentor and captcha. Both can be easily installed via pip. Augmentor offers various methods for synthesizing images, and the three methods I used were Distortion, Skew and Tilt, and Rotate. For more details, please refer to the aug_data.py script. Captcha can automatically generate captcha images, and I noticed that the images it generates are quite similar to the training dataset provided by the teaching assistants. Therefore, I attempted to use the generated captcha images for training and found that it produced significantly good results. For more details, please refer to the captcha_gen.py script.

Finally, there are some configurations and hyperparameters that I experimented with, leading to various results and findings. These will be discussed in the following sections.

Environment Details:

Training, Inferencing:

Google Colab

Generating Data:

python 3.9.12 augmentor 0.2.12 captcha 0.4 pandas 1.4.2 pillow 9.0.1

Experimental Setting and Implementation Details:

- A. Common Setting, used in all experiments:
 - 1. Pictures normalize to mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]
 - 2. Use ResNet34 network with dropout=0.5
 - 3. Train test split = 8:2
 - 4. Training epoch=50 for task 1, 2; epoch=75 for task 3
 - 5. Learning rate = 1e-3
 - 6. Use lr_scheduler.StepLR, step=10 for task 1, 2; step=15 for task 3; gamma=0.5
- B. Data Augmentation, generating more data by:
 - 1. Augmentor (pip install Augmentor)
 - I. Distortion
 - II. Skew & Tilt
 - III. Rotate
 - 2. captcha (pip install captcha)
- C. Optimizer (provided by pytorch 2.0.0):
 - 1. Adam(model.parameters(), lr=lr)
 - 2. RAdam(model.parameters(), lr=lr, betas=(0.9, 0.999), weight_decay=6.5e-4)
 - 3. AdamW(model.parameters(), lr=lr)
 - 4. NAdam(model.parameters(), lr=lr, betas=(0.9, 0.999), weight decay=6.5e-4)
- D. Batch Size and Resize:
 - 1. Pictures resize to 32*32, batch size=256
 - 2. No resize, batch size=64

Experimental Results:

model	#total training data	#generated data	Data Augmented Method	Optimizer	Batch Size, Resize	Test Score
1	Task1: 9639	Task1: 10000	B.1.I	C.1	D.1	0.9078
	Task2: 11956	Task2: 12500				
	Task3: 19242	Task3: 20000				
2	Task1: 4813	Task1: 4000	B.1.I + B.1.II	C.1	D.1	0.8898
	Task2: 6035	Task2: 5000				
	Task3: 9547	Task3: 8000				
3	Task1: 6431	Task1: 6000	B.1.I + B.1.II + B.1.III	C.1	D.1	0.8808
	Task2: 7999	Task2: 7500				
	Task3: 12804	Task3: 12000				
4	Task1: 7652	Task1: 7500	B.1.I	C.1	D.1	0.895
	Task2: 7964	Task2: 7500				
	Task3: 12807	Task3: 12000				
5	Task1: 10045	Task1: 10500	B.1.I	C.1	D.1	0.911
	Task2: 10350	Task2: 10500				
	Task3: 17656	Task3: 18000				
6	Task1: 18388	Task1: 21000	B.1.I	C.1	D.1	0.9182
	Task2: 18859	Task2: 21000				
	Task3: 31973	Task3: 36000				
7	Task1: 34446	Task1: 41000	B.1.I + B.2	C.1	D.1	0.943
	Task2: 34774	Task2: 41000				
	Task3: 59902	Task3: 71000				
8	Task1: 34446	Task1: 41000	B.1.I + B.2	C.2	D.1	0.95
	Task2: 34774	Task2: 41000				
	Task3: 59902	Task3: 71000				
9	Task1: 34446	Task1: 41000	B.1.I + B.2	C.3	D.1	0.9412
	Task2: 34774	Task2: 41000				
	Task3: 59902	Task3: 71000				
10	Task1: 34446	Task1: 41000	B.1.I + B.2	C.4	D.1	0.9442
	Task2: 34774	Task2: 41000				
	Task3: 59902	Task3: 71000				
11	Task1: 67223	Task1: 82000	B.1.I + B.2	C.2	D.1	0.94360
	Task2: 67591	Task2: 82000				
	Task3: 116772	Task3: 142000				
12	Task1: 34446	Task1: 41000	B.1.I + B.2	C.2	D.2	0.971
	Task2: 34774	Task2: 41000				
	Task3: 59902	Task3: 71000				

Result Analysis:

Based on the experimental data in the table, I tested three different Augmentor methods in the first three experimental setups. I found that Distortion yielded the best results, achieving an accuracy of 90.78% when the data generated by Distortion was mixed with the original training dataset. Interestingly, when I combined the remaining two methods with more data, the accuracy actually decreased. This indicates that the Distortion method is capable of generating more effective data. Consequently, I decided to use this method for all subsequent experiments.

In experiments 4, 5, and 6, I further attempted to generate more data using the Distortion method. As the amount of data increased, the accuracy also improved, but at a gradually slowing rate, and it required more training time. After weighing the pros and cons, I decided to generate 21,000 samples for task 1, 21,000 samples for task 2, and 36,000 samples for task 3. I also applied this setting in subsequent experiments.

In experiment 7, I attempted to incorporate data generated by captchas, and I found a significant improvement in the results. The accuracy jumped from 91.82% to 94.3%. This clearly indicates that the data generated by captchas is also highly effective for training purposes. Therefore, I will continue to apply this setup in subsequent experiments. It is worth noting that the current training data consists of the original training dataset, data generated by the Augmentor method, and data generated by captchas.

In experiments 8, 9, and 10, I tried various different optimizers. The results of the experiments showed that RAdam performed the best, with an accuracy of 95%.

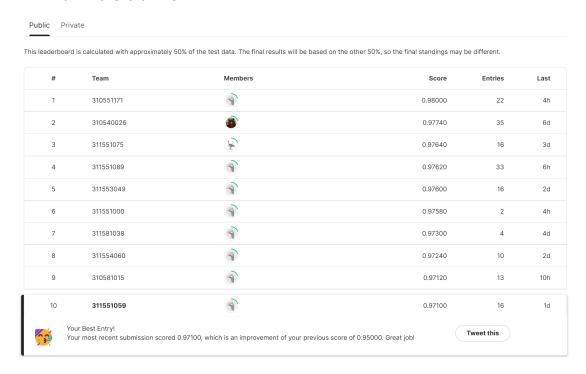
In experiment 11, I attempted to generate more data using captchas. However, there was a slight decrease in accuracy instead. This suggests that generating too much additional data may lead to larger errors.

In experiment 12, I tried removing the resize operation. This required reducing the batch size due to limited GPU memory. However, I found that removing the resize operation and reducing the batch size resulted in even higher accuracy, reaching 97.1%.

Apart from the aforementioned experimental settings, there are many other variables that can be adjusted. However, due to time constraints, I only attempted the above set of experiments.

Kaggle Submission Screenshot:

Rank 10 in 2023/6/6 12:52am.



How to run inference:

- 1. Open Google Colab
- 2. Download the model weights:

https://drive.google.com/drive/folders/1rdE0j3o0dP4bFbutZbWm 7yabCYItZjo?usp=sharing

3. Modify the path including testing dataset, sample_submission path, save to csv path, and the model weights path.

```
[9] TEST_PATH = "/content/dataset/test"

SUBMISSION_CSV_PATH = "/content/dataset/sample_submission.csv"

SAVE_TO_CSV_PATH = "/content/drive/MyDrive/submission.csv"

TASK1_MODEL_PATH = "/content/drive/MyDrive/models_best/task1.pt"

TASK2_MODEL_PATH = "/content/drive/MyDrive/models_best/task2.pt"

TASK3_MODEL_PATH = "/content/drive/MyDrive/models_best/task3.pt"
```

4. Run all.