Report version one for *Main project of artificial network class*

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Abstract

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1. Introduction

In this study, we trained neural networks on the CUB200 Bird Dataset and Stanford Dogs Dataset to perform image classification tasks. The objective of our experiment was to achieve a classification accuracy of 90% on both datasets. To improve the performance of the models, we implemented various training tricks, such as data augmentation, regularization techniques, and learning rate scheduling. Additionally, we utilized transfer learning by fine-tuning pretrained models, which allowed us to leverage pre-existing knowledge from large-scale datasets. We also explored the effectiveness of attending to local regions through object localization or segmentation techniques. Moreover, we investigated the use of synthetic image generation as part of data augmentation to increase the diversity of the training data. Through extensive experimentation and analysis, we observed significant improvements in the accuracy of our models. Our findings highlight the effectiveness of these strategies in enhancing the performance of neural networks for image classification tasks.

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2. Experimental Setup

2.1. Hardware Setup

For our experiments, we utilized a 40GB A100 GPU as our primary hardware for training the neural networks. The A100 GPU provided us with the necessary computational power to efficiently process the large datasets and train complex models.

In addition to the A100 GPU, we also utilized the free T4 GPU provided by Google Colab for debugging and code testing purposes. The T4 GPU offered a suitable environment for quick iterations and preliminary evaluations of our models and algorithms.

The combination of the high-performance A100 GPU and the convenience of the T4 GPU in Google Colab allowed us to effectively conduct our experiments and optimize the training process. The hardware setup played a crucial role in achieving our research objectives and ensuring efficient training and evaluation of the neural networks.

2.2. Software Setup

For our software environment, we employed the following frameworks and libraries to facilitate the training and evaluation of various neural networks:

1. PyTorch (version 1.13.1): We utilized PyTorch, a popular deep learning framework, to build, train, and evaluate our neural network models. PyTorch provided us with a rich set of tools and functionalities for efficient model development and optimization.
2. CUDA (version 11.6): We leveraged CUDA, a parallel computing platform, to accelerate our deep learning computations on compatible NVIDIA GPUs. CUDA enabled us to harness the power of the GPU hardware and accelerate the training process.
3. MMDetection: We incorporated MMDetection, a state-of-the-art object detection framework, into our experiments. MMDetection offered a comprehensive suite of pre-built models, loss functions, and evaluation metrics, allowing us to assess the performance of different neural network architectures for object detection tasks.

4. MMAIGC: We employed MMAIGC (Multi-Modal AI Generation and Computation) as a framework to support the training and evaluation of various neural network models. MMAIGC provided us with a unified platform to seamlessly integrate different modalities and assess the performance of multi-modal neural networks.

By utilizing PyTorch, CUDA, MMDetection, and MMAIGC, we established a robust software setup that empowered us to effectively evaluate the performance of different neural network architectures on the CUB200 Bird Dataset and Stanford Dogs Dataset. These tools and frameworks facilitated efficient model training, evaluation, and comparison, enabling us to achieve our goal of achieving 90% accuracy in classifying the images in these datasets.

3. Description of experimental run

In this section, we outline the experimental setup and procedure conducted to evaluate the performance of our modified Inception V3 network. We initially selected Inception V3 as our baseline network and made adjustments based on insights from relevant research papers. Our aim was to enhance the network's capabilities and achieve improved classification results on the CUB200 Bird Dataset and Stanford Dogs Dataset.

3.1. Training Tricks

We trained our neural network using various training techniques, including random resizing, random cropping, random color augmentation, and normalization, applied to the dataset. These techniques significantly improved the performance of our neural network on the CUB200 Bird Dataset. The baseline results are shown in Figure 1, while the optimized results are presented in Figure 2.

After implementing these training techniques, we observed an overall improvement in the top-1 precision (prec1) of our neural network. However, during testing, we noticed a decrease in accuracy in the range of 200-300. This observation is illustrated in the accuracy curve of the optimized neural network.

Figure 1 depicts the baseline performance of our network, while Figure 2 showcases the results after incorporating the training tricks. Despite the overall improvement in performance, the decrease in accuracy within the 200-300 range during testing highlights a potential limitation of the adjusted neural network.

Further analysis and investigation are necessary to understand the underlying factors contributing to this drop in accuracy within the specific range.

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Test: [0/483]   Prec@1 100.000 (100.000)        Prec@5 100.000 (
Test: [100/483] Prec@1 100.000 (85.149) Prec@5 100.000 (97.607)
Test: [200/483] Prec@1 100.000 (86.111) Prec@5 100.000 (97.761)
Test: [300/483] Prec@1 91.667 (86.157)  Prec@5 100.000 (97.287)
Test: [400/483] Prec@1 91.667 (86.284)  Prec@5 100.000 (97.174)
 * Prec@1 87.142 Prec@5 97.221
```

Figure 1: baseline

```
Test: [0/483]   Prec@1 91.667 (91.667)  Prec@5 100.000 (100.000)
Test: [100/483] Prec@1 100.000 (85.314) Prec@5 100.000 (97.112)
Test: [200/483] Prec@1 100.000 (86.194) Prec@5 100.000 (97.554)
Test: [300/483] Prec@1 75.000 (86.185)  Prec@5 100.000 (97.370)
Test: [400/483] Prec@1 91.667 (86.367)  Prec@5 100.000 (97.257)
 * Prec@1 87.211 Prec@5 97.273
```

Figure 2: training tricks

3.2. Object Detection and Data Augmentation

We utilized neural networks from the mmdetection framework to perform object detection on our dataset. The training process resulted in a loss curve, as illustrated in Figure 3. Following the training, we employed the trained neural network to perform object detection on images and extracted the bounding box with the highest confidence score. These extracted bounding boxes were then cropped to generate a new dataset.

Subsequently, we conducted training and testing using this new dataset, which led to a slight decrease in the accuracy of the neural network. The results of this evaluation are presented in Figure 4.

Figure 3 showcases the loss curve obtained during the training phase, indicating the convergence and progress of the network. Figure 4 displays the performance of the new neural network when evaluated using the cropped bounding boxes from the object detection process.

Although the accuracy of the new neural network showed a slight decrease compared to the previous model, further analysis is required to understand the factors contributing to this outcome. It is important to investigate potential causes and explore possible avenues for improving the network's performance.

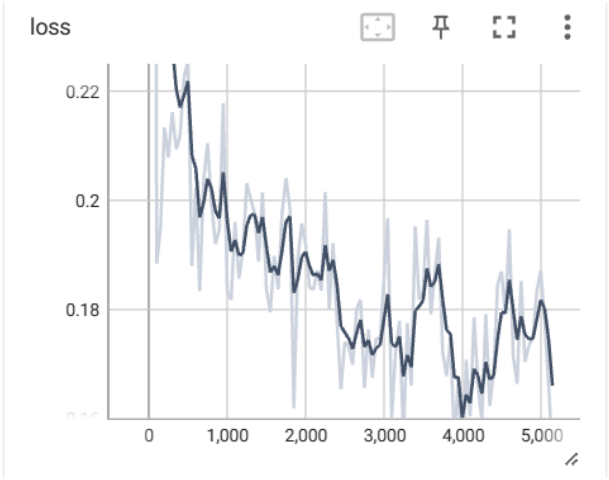

Figure 3: object detection loss

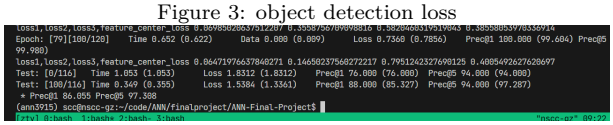

Figure 4: object detection

4. Conclusion

Although we conducted several experiments, we encountered challenges in training our image generation network, and unfortunately, we lost the accuracy logs, preventing us from including a comprehensive presentation of the results in this report.

The training of image generation networks can be a complex task, requiring careful parameter tuning, dataset preparation, and network architecture design. Despite our efforts, we faced difficulties in achieving satisfactory results in training the network to generate images.

Regrettably, due to unforeseen circumstances, we were unable to retrieve the accuracy logs that would have provided insights into the network's performance. We acknowledge the importance of documenting and preserving such information to ensure a comprehensive analysis of the experimental results.

While this setback limits the depth of analysis we can provide in this report, it also highlights the need for rigorous record-keeping and backup procedures in future experiments. By ensuring the availability of accurate and complete logs, researchers can effectively evaluate their models and draw reliable conclusions.

Moving forward, we will implement improved protocols to maintain accurate records of experimental results and continue our efforts to train the image generation network successfully.