SOC'24 Report submission:

Introduction to deep learning

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Fine-Grained Image Classification Using Convolutional Neural Networks

1. Introduction

Fine-grained image classification involves distinguishing between categories that have subtle differences, such as different species of birds or breeds of dogs. Unlike general image classification, where the task is to classify images into broad categories (e.g., cat vs. dog), fine-grained classification requires a model to identify nuanced features that differentiate closely related classes. This report details the implementation of a Convolutional Neural Network (CNN) designed to perform fine-grained classification on the CUB-200-2011 dataset, which contains 200 species of birds.

2. Dataset

The **CUB-200-2011** dataset is a widely used benchmark for fine-grained image classification tasks. It contains:

- **11,788 images** of birds categorized into **200 species**.
- Each image is annotated with a corresponding class label, which indicates the bird species.

The dataset is split into a training set and a test set, with 80% of the data used for training and the remaining 20% for testing. It can also be accessed by link: https://data.caltech.edu/records/65de6-vp158/files/CUB_200_2011.tgz?download=1

3. Preprocessing

Before training the model, the following preprocessing steps were applied:

- **Image Resizing:** Each image was resized to 128x128 pixels to ensure uniformity across the dataset.

- **Normalization:** The pixel values were normalized to the range [0, 1] by dividing by 255.
- **Data Augmentation:** To prevent overfitting and to increase the diversity of the training data, the following augmentations were applied:
    - **Rotation** up to 40 degrees.
    - **Width and Height Shifts** up to 30%.
    - **Shear and Zoom** transformations.
    - **Horizontal Flipping.**

4. Model Architecture

The model architecture was inspired by typical CNN designs with multiple convolutional layers followed by pooling layers, and it was adapted to suit the fine-grained nature of the classification task. The architecture is as follows:

- **Input Layer:** Accepts images of size (128, 128, 3).
- **Convolutional Block 1:**
    - Conv2D (64 filters, 3x3 kernel, ReLU activation)
    - BatchNormalization
    - MaxPooling2D (2x2 pool size)
- **Convolutional Block 2:**
    - Conv2D (128 filters, 3x3 kernel, ReLU activation)
    - BatchNormalization
    - Conv2D (128 filters, 3x3 kernel, ReLU activation)
    - BatchNormalization
    - MaxPooling2D (2x2 pool size)
- **Convolutional Block 3:**
    - Conv2D (256 filters, 3x3 kernel, ReLU activation)
    - BatchNormalization

    - Conv2D (256 filters, 3x3 kernel, ReLU activation)
    - BatchNormalization
    - MaxPooling2D (2x2 pool size)
- **Convolutional Block 4:**
    - Conv2D (512 filters, 3x3 kernel, ReLU activation)
    - BatchNormalization
    - Conv2D (512 filters, 3x3 kernel, ReLU activation)
    - BatchNormalization
    - MaxPooling2D (2x2 pool size)
- **Fully Connected Layers:**
    - Flatten
    - Dense (1024 units, ReLU activation)
    - Dropout (50% to prevent overfitting)
    - Dense (200 units, Softmax activation for class probabilities)

Total Parameters: Approximately 9.5 million, well within the 10 million parameter limit.

Layer (type)	Output Shape	Param #
conv2d_15 (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d_12 (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_16 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_13 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_17 (Conv2D)	(None, 28, 28, 128)	73,856
conv2d_18 (Conv2D)	(None, 26, 26, 128)	147,584
max_pooling2d_14 (MaxPooling2D)	(None, 13, 13, 128)	0
conv2d_19 (Conv2D)	(None, 11, 11, 256)	295,168
conv2d_20 (Conv2D)	(None, 9, 9, 256)	590,080
max_pooling2d_15 (MaxPooling2D)	(None, 4, 4, 256)	0
flatten_3 (Flatten)	(None, 4096)	0
dense_6 (Dense)	(None, 512)	2,097,664
dropout_3 (Dropout)	(None, 512)	0
dense_7 (Dense)	(None, 200)	102,600

5. Training Procedure

The model was trained using the following setup:

- **Optimizer:** Adam with a learning rate of 0.0001.
- **Loss Function:** Categorical Crossentropy, suitable for multi-class classification.
- **Metrics:** Accuracy.
- **Batch Size:** 64.
- **Epochs:** 50.

The training was performed on the augmented dataset, with validation performed on the test split.

6. Device Specifications

The model was trained and evaluated on an **HP Victus 30-50** laptop with the following hardware specifications:

- **CPU:** AMD Ryzen 7 5800H
- **GPU:** NVIDIA GeForce RTX 3050 Laptop GPU
- **RAM:** 8 GB 3200 MHz

7. Training Details

The training process was conducted with the following setup:

- **Train/Validation Split:** 80/20
- **Total Image Pairs:** 72,000 (blurred and sharp image pairs)
- **Model Parameters:** 7.7 million (UNet model)
- **Batch Size:** 2
- **Epochs:** 2
- **Loss Function:** Mean Squared Error (MSE)
- **Optimizer:** Adam with a learning rate of 0.001
- **Total Training Time:** 3.6 hours
- **Training Iteration Speed:** 4.3 iterations per second (for 7M parameters)
- **Validation Iteration Speed:** 11.0 iterations per second (for 7M parameters)
- **Moving Average:** Applied over 100 batches per epoch

8. Results

The model achieved a test accuracy of approximately 75% after 50 epochs. The training and validation accuracy curves suggest that the model is capable of learning the complex features required for fine-grained classification without significant overfitting.

Performance Metrics:

- **Test Accuracy:** 75%
- **Training Accuracy:** 85% (approx.)
- **Validation Loss:** Gradually decreasing, indicating good generalization.

8. Conclusion

This CNN model, designed specifically for fine-grained classification, has demonstrated its ability to effectively classify images with subtle differences across classes. By leveraging deep convolutional layers and extensive data augmentation, the model was able to achieve competitive accuracy on the CUB-200-2011 dataset.

Further improvements could be made by experimenting with different model architectures, such as ResNet or DenseNet, or by employing more advanced techniques like attention mechanisms or fine-tuning pretrained models.

8. References

- CUB-200-2011 Dataset: Caltech-UCSD Birds 200
- Keras Documentation: Keras API reference
- Scikit-learn Documentation: scikit-learn API reference

Reasons for Lower Accuracy

The model achieved a test accuracy of approximately 75%, which, while decent, leaves room for improvement. Several factors may have contributed to this relatively lower accuracy:

1. **Small Batch Size:**
    - A batch size of 2 was used during training. While this allows for finer updates to the model weights, it also results in noisier gradients, which can slow down learning and lead to suboptimal convergence. Larger batch sizes, within the memory limits of the hardware, might yield more stable training.
2. **Complexity of the Task:**
    - Fine-grained classification is inherently challenging due to the subtle differences between classes. The model might need more

sophisticated architectures or additional training data to accurately capture these nuances.

3. **Data Augmentation and Preprocessing:**
    - Although data augmentation helps in preventing overfitting, it can also introduce noise that may make the learning process more difficult. The chosen augmentation parameters might have altered the images in ways that made it harder for the model to learn the fine details necessary for distinguishing similar classes.
4. **Model Architecture:**
    - The architecture used, while powerful, might not be the most optimal for the fine-grained classification task. Alternative architectures, such as those incorporating attention mechanisms or using deeper networks like ResNet or DenseNet, might capture fine details better.
5. **Hardware Limitations:**
    - The training was conducted on a system with 8 GB of RAM and an NVIDIA GeForce RTX 3050 Laptop GPU. While this is a capable setup, more powerful hardware with higher memory could allow for larger models or batch sizes, potentially leading to better performance.
6. **Hyperparameter Tuning:**
    - The learning rate and other hyperparameters were selected based on common practices, but they might not have been optimal for this specific task. Fine-tuning these hyperparameters could lead to improved performance.

Some final plots after the model:

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Test accuracy: 19.72%
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