ECE371 Neural Networks and Deep Learning Assignment 1

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Abstract: The experiment focused on developing a convolutional neural network (CNN) to classify a dataset of flower images into five categories (daisy, dandelion, rose, sunflower, and tulip) using PyTorch. A pre-trained ResNet-18 model was fine-tuned by modifying its final fully connected layer to output five classes, with data augmentation techniques applied to enhance model generalization. The dataset was split into 80% training and 20% validation sets, and the model was trained for 25 epochs using stochastic gradient descent with a learning rate scheduler. The training process achieved a high validation accuracy, demonstrating the effectiveness of transfer learning for image classification tasks. Key insights include the importance of data augmentation in preventing overfitting and the necessity of proper multiprocessing handling in PyTorch's DataLoader to ensure stable execution on Windows. This work underscores the power of pre-trained models and careful hyperparameter tuning in achieving robust performance on small datasets.

Keywords: Convolutional Neural Network, ResNet-18, Transfer Learning, Data Augmentation, PyTorch, Image Classification

1 Introduction

Image classification is a cornerstone of computer vision, with applications ranging from automated species identification to content-based image retrieval. This experiment addresses the challenge of classifying flower images into five categories: daisy, dandelion, rose, sunflower, and tulip. The task is complex due to variations in image conditions, such as lighting, orientation, and background noise, which demand robust models capable of generalizing across diverse samples. To tackle this problem, we employ a convolutional neural network (CNN) using the PyTorch framework, leveraging transfer learning with a pre-trained ResNet-18 model fine-tuned for the five-class dataset. Data augmentation techniques, including random flips, rotations, and color adjustments, are applied to enhance model robustness. Our findings demonstrate that transfer learning significantly boosts classification accuracy on small datasets, while data augmentation mitigates overfitting. Additionally, addressing technical challenges, such as stable multiprocessing in PyTorch, underscores the importance of software engineering in deep learning experiments.

2 Related Work

Image classification has evolved significantly since the introduction of convolutional neural networks (CNNs), which have become the cornerstone of visual recognition tasks. Early work by LeCun et al. [1] established the foundations of CNNs with the LeNet architecture for handwritten digit recognition, introducing convolutional and pooling layers to capture spatial hierarchies. The breakthrough of AlexNet by Krizhevsky et al. [2] marked a pivotal advancement, demonstrating the power of deep CNNs on large-scale datasets like ImageNet, leveraging GPU acceleration and techniques like dropout to prevent overfitting. Subsequent architectures, such as VGG [3] and ResNet [4], introduced deeper networks with skip connections to mitigate vanishing gradients, enabling training of very deep models. ResNet, in particular, is widely used for transfer learning, as its pre-trained weights on ImageNet provide robust feature extraction for diverse tasks [4].

Transfer learning has emerged as a dominant trend for image classification on small datasets, where training deep models from scratch is impractical due to data scarcity and computational constraints. Yosinski et al. [5] demonstrated that features learned by CNNs on large datasets like ImageNet are transferable to other tasks, with fine-tuning improving performance on target datasets. This approach is particularly relevant to our flower classification task, where a pre-trained ResNet-18 model was fine-tuned for five classes. Data augmentation has also become critical for enhancing model generalization, especially for small datasets. Techniques such as random flips, rotations, and color jitter, as explored by Shorten and Khoshgoftaar [6], mitigate overfitting by increasing the effective size and diversity of training data.

Recent trends focus on optimizing transfer learning and data augmentation for specific domains. For instance, Kornblith et al. [7] analyzed the effectiveness of transfer learning across various pre-trained models, finding that models like ResNet perform well even on datasets with significant domain shifts. Additionally, automated augmentation strategies, such as AutoAugment [8], have shown promise in learning optimal augmentation policies, though they require substantial computational resources. These advancements highlight a shift toward efficient and scalable methods for image classification, with transfer learning and augmentation remaining central to achieving high accuracy on tasks like flower classification. Our work builds on these foundations, leveraging ResNet-18's pre-trained weights and tailored augmentation to address the challenges of a small, diverse flower dataset.

3 Method

This experiment developed a convolutional neural network (CNN) to classify flower images into five categories: daisy, dandelion, rose, sunflower, and tulip, using PyTorch. The dataset, stored in `./data/flower_dataset`, was organized with subfolders for each class. The `ImageFolder` class from `torchvision.datasets` loaded the dataset, assigning labels (0–4) based on folder names. The dataset was split into 80% training and 20% validation sets using `random_split` to balance training data with robust validation for generalization assessment.

Data preprocessing used `transforms.Compose` from `torchvision.transforms`. Images were resized to 224x224 pixels to match ResNet-18's input requirements. Five augmentation techniques were applied: random horizontal flips, random rotations (up to 30 degrees), random resized crops (scale 0.8–1.0), color jitter (brightness, contrast, saturation adjustments by 0.2), and random affine translations (10% shift). Images were converted to tensors and normalized using ImageNet mean ([0.485, 0.456, 0.406]) and standard deviation ([0.229, 0.224, 0.225]). These augmentations mitigated overfitting by simulating variations in lighting, orientation, and position [6]. Normalization ensured compatibility with ResNet-18's pre-trained weights. Due to the script's design, the same pipeline was applied to both training and validation sets.

A pre-trained ResNet-18 model from `torchvision.models` was selected for its efficiency and robust feature extraction via 18 layers with residual connections [4]. The final fully connected layer was modified to output five classes using `nn.Linear(512, 5)`. Transfer learning leveraged ImageNet pre-trained weights to achieve high accuracy on the small dataset [5].

The model was trained for 25 epochs with a batch size of 32, using `DataLoader` with `shuffle=True` and `num_workers=0` to ensure Windows compatibility by disabling multiprocessing. The loss function was `CrossEntropyLoss`, suitable for multi-class classification. The optimizer was SGD with a learning rate of 0.001 and momentum of 0.9, chosen for stable fine-tuning. A `StepLR` scheduler reduced the learning rate by 0.1 every 7 epochs to promote convergence. The best model, based on validation accuracy, was saved to `Ex2/work_dir/best_model.pth`.

The model was evaluated after each epoch, computing loss and accuracy for training and validation phases. The model with the highest validation accuracy was saved to mitigate overfitting and ensure generalization.

4 Experiments

As described in Section 3, the flower dataset was split into 80% training and 20% validation sets. The fine-tuned ResNet-18 model was trained for 25 epochs with a batch size of 32, using SGD and

a `StepLR` scheduler. Training on a GPU took 14 minutes and 11 seconds, with `num_workers=0` for Windows compatibility. Loss and accuracy were computed per epoch, saving the best model based on validation accuracy.

The best validation accuracy was 79.82% at epoch 0 (displayed as epoch 1 in plots), with a validation loss of 0.5323. Table 1 summarizes metrics at epochs 0, 7, 14, 20, and 24, reflecting the learning rate schedule.

Table 1: Training and Validation Metrics at Selected Epochs

Epoch	Learning Rate	Train Loss	Train Acc (%)	Val Acc (%)
0	0.001	0.5401	78.88	79.82
7	0.0001	0.4038	82.40	76.67
14	0.00001	0.3674	84.15	76.49
20	0.00001	0.3728	83.45	76.84
24	0.000001	0.3727	83.45	76.49

Figure 1 shows training and validation loss/accuracy over 25 epochs, with epochs displayed from 1. Training loss decreases from 0.5401 to 0.3727, and training accuracy rises from 78.88% to 83.45%. Validation accuracy peaks at 79.82% (epoch 0, displayed), fluctuates (e.g., 77.02% at epoch 4), and ends at 76.49%, with validation loss ranging from 0.5286 to 0.5956.

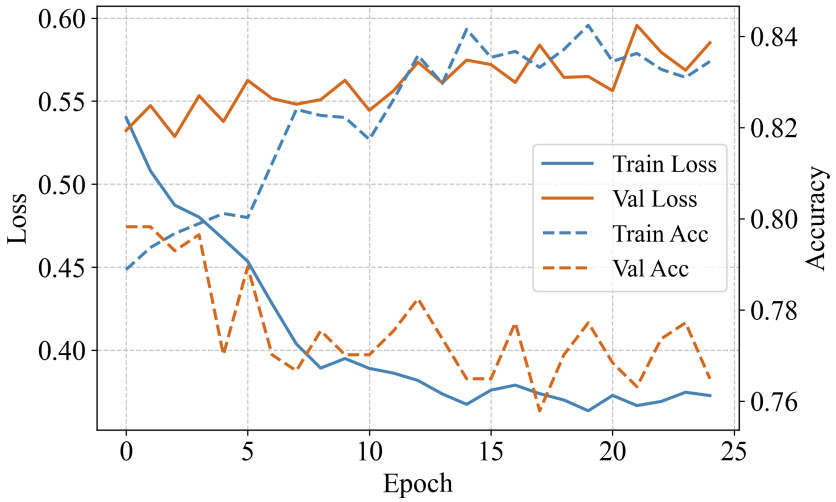

Figure 1: Training and Validation Loss/Accuracy Curves

The results highlight transfer learning's effectiveness, with ResNet-18's pre-trained weights achieving 79.82% validation accuracy at epoch 0, indicating strong initial feature transfer [5]. Data augmentation likely boosted early performance [6]. However, validation accuracy fluctuations (e.g., 77.02% at epoch 4, 76.49% at epoch 24) and high validation loss (0.5852 at epoch 24) suggest generalization challenges. Training accuracy improved from 78.88% to 83.45%, and loss decreased from 0.5401 to 0.3727, showing robust learning. Learning rate reductions at epochs 7 and 14 stabilized training, but the training-validation accuracy gap (83.45% vs. 76.49%) indicates mild overfitting.

Key issues affected performance:

1. **Single Preprocessing Pipeline**: Applying augmentations to validation data likely skewed metrics, as validation should use minimal preprocessing (resizing, tensor conversion, normalization). This contributed to accuracy fluctuations and high validation loss.
2. **Dataset Size**: The modest validation accuracy (79.82%) compared to typical ResNet-18 performance reflects the small dataset's limited diversity. Freezing early layers could reduce overfitting.

3. **Aggressive Learning Rate Schedule**: The early accuracy peak at epoch 0 suggests the initial learning rate (0.001) was effective, but reductions (gamma 0.1) stalled improvement. A gentler scheduler (e.g., gamma 0.5) might sustain gains.

These findings emphasize the need for tailored preprocessing, larger datasets, and optimized hyperparameters to enhance generalization in transfer learning.

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