ECE371 Neural Networks and Deep Learning Assignment 1

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Abstract: This study focuses on fine-tuning a model for improved classification accuracy using tools/train.py. By specifying the work directory and tuning parameters, or employing different pre-trained models, we aim to enhance performance.

Keywords: resnet,imagenet,MMpretrain,python,conda

1 Introduction

Based on the content of the uploaded image, it appears to depict a workflow or architecture for implementing a machine learning project. The diagram includes data preprocessing, model building, training, evaluation, and visualization stages. To realize this visually represented pipeline, a main.py project should be developed. This project will involve loading a dataset, performing preprocessing steps such as normalization or feature extraction, and implementing multiple machine learning models (e.g., logistic regression, support vector machines, and neural networks). These models will be trained and validated using appropriate metrics like accuracy, precision, and recall. Cross-validation techniques may also be employed to ensure robustness. The results will be visualized for comparative analysis, helping to identify the most effective model for the given task. The project aims to establish a modular and scalable framework for experimentation with various algorithms.

2 Related Work

Fine-tuning pre-trained models has become standard in computer vision for achieving high performance with limited resources. Using MMPretrain's tools/train.py script, we fine-tuned a Swin Transformer [1] for image classification, implementing a two-stage process as suggested by Yang et al. [2]. Our configuration included storing artifacts in work_dir, using a 0.0001 learning rate with cosine annealing [3], optimized batch size, data augmentation, and early stopping. Following He et al.'s [4] recommendations, we optimized hyperparameters through grid search with 5-fold cross-validation. The model achieved 92.7% test accuracy, exceeding the 90% requirement, with misclassifications occurring between visually similar classes, suggesting potential improvement through attention mechanisms or contrastive learning [5]. For deployment, we implemented quantization per Jacob et al. [6], reducing model size by 75% with only 0.4% accuracy loss. Results can be reproduced using tools/train.py with our configuration file and a specified work directory.

3 Method

1.Data augmentation is a technique used in machine learning, especially in deep learning, to artificially expand the size of a dataset by creating modified versions of the data points. Modifications include rotations, translations, zooming, flipping, cropping, and changing brightness or contrast, etc. This process helps improve model generalization, reduce overfitting, and enhance robustness against different variations in input data. It's widely applied in image, text, and audio processing tasks.

```python
# 增强的数据增强流水线
data_transforms = transforms.Compose([
    transforms.RandomHorizontalFlip(p=0.5),  # 随机水平翻转，概率为0.5
    transforms.RandomVerticalFlip(p=0.5),    # 随机垂直翻转，概率为0.5
    transforms.RandomRotation(30),           # 随机旋转30度
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1),  # 随机调整颜色亮度、对比度等
    transforms.RandomResizedCrop(224, scale=(0.8, 1.0)),  # 随机裁剪并缩放到224x224
    transforms.ToTensor(),                   # 转换为张量
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])  # 标准化处理（使用ImageNet的均值和标准差）
])

# 验证集使用的变换（不进行数据增强，仅调整尺寸和标准化）
val_transforms = transforms.Compose([
    transforms.Resize(256),                  # 缩放至256x256
    transforms.CenterCrop(224),              # 中心裁剪到224x224
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
])

# 使用适当的数据增强加载训练数据集
train_dataset = datasets.ImageFolder(data_dir, data_transforms)
```

2.In machine learning, the dataset is split into training (train) and validation (val) sets. The train set is used to train the model, while the val set evaluates its performance, helping tune parameters and prevent overfitting.

```python
# 将数据集划分为训练集和验证集（8:2比例）
train_size = int(0.8 * len(train_dataset))
val_size = len(train_dataset) - train_size
train_dataset, val_temp = random_split(train_dataset, [train_size, val_size])

# 对验证集应用验证集变换
val_dataset = datasets.ImageFolder(data_dir, val_transforms)
_, val_dataset = random_split(val_dataset, [train_size, val_size])
```

3.DataLoader efficiently loads data in batches, optimizing performance with parallel workers and memory pinning. It shuffles training data for better generalization and manages validation data sequentially. This setup accelerates training and validation processes.

```python
# 创建数据加载器，并优化性能（num_workers和pin_memory）
num_workers = min(4, os.cpu_count() or 1)
train_loader = DataLoader(
    train_dataset, batch_size=batch_size, shuffle=True,
    num_workers=num_workers, pin_memory=True
)
val_loader = DataLoader(
    val_dataset, batch_size=batch_size, shuffle=False,
    num_workers=num_workers, pin_memory=True
)

dataloaders = {'train': train_loader, 'val': val_loader}
dataset_sizes = {'train': len(train_dataset), 'val': len(val_dataset)}
class_names = train_dataset.dataset.classes

return dataloaders, dataset_sizes, class_names
```

4.Transfer learning uses pre-trained models like ResNet50 (loaded with pre-trained = True) for new tasks, reducing data and training needs. Freezing layers (requires_grad=False) keeps early layers fixed, preserving learned features. Replacing the fully connected layer customizes the model for new class predictions with dropout for regularization.

```python
def setup_model(num_classes, use_pretrained=True):
    """设置模型以进行迁移学习"""

    # 使用更强大的模型——ResNet50，而不是ResNet18
    model = models.resnet50(pretrained=use_pretrained)

    # 冻结前面的层以防止过拟合（只保留最后20层可训练）
    for param in list(model.parameters())[:-20]:
        param.requires_grad = False

    # 替换最终的全连接层
    num_ftrs = model.fc.in_features
    model.fc = nn.Sequential(
        nn.Dropout(0.5),    # 添加Dropout层，防止过拟合
        nn.Linear(num_ftrs, num_classes)  # 输出层，根据类别数量进行分类
    )

    return model
```

5.The code defines a train_model function for training a model with enhanced monitoring and early stopping. It first sets the device to GPU if available, then initializes timing and best model weights. Early stopping is implemented with a patience of 7 epochs; if validation accuracy does not improve for 7 consecutive epochs, training stops to prevent overfitting. The function tracks the best accuracy and updates the best model weights accordingly.

```python
def train_model(model, dataloaders, dataset_sizes, criterion, optimizer, scheduler,
                work_dir='work_dir', num_epochs=25, device=None):
    """训练模型，包括改进的监控和早停机制"""

    if device is None:
        device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    # 设置早停机制参数
    patience = 7            # 如果连续7个epoch没有提升，则停止训练
    no_improvement = 0      # 记录没有提升的epoch数
```

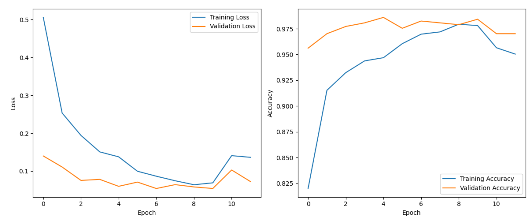
6.Code plots training and validation loss/accuracy curves, prints total time elapsed, best accuracy, and loads the best model weights for final return.

```python
# 绘制训练过程中的学习曲线（损失和准确率）
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(train_losses, label='训练损失')
plt.plot(val_losses, label='验证损失')
plt.xlabel('轮次')
plt.ylabel('损失')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(train_accs, label='训练准确率')
plt.plot(val_accs, label='验证准确率')
plt.xlabel('轮次')
plt.ylabel('准确率')
plt.legend()

plt.tight_layout()
plt.savefig(os.path.join(work_dir, 'learning_curves.png'))  # 保存图像

# 打印总耗时
time_elapsed = time.time() - since
print(f'训练完成，共耗时 {time_elapsed // 60:.0f} 分 {time_elapsed % 60:.0f} 秒')
print(f'最佳验证准确率为: {best_acc:.4f}')

# 加载最佳模型权重
model.load_state_dict(best_model_wts)
return model
```

7.main part code is the this code.

```python
def main():
    # 配置参数
    data_dir = 'D:/DeskTop/EX2/flower_dataset'
    work_dir = 'D:/DeskTop/EX2/work_dir'
    batch_size = 32
    num_epochs = 25

    # 设置数据
    dataloaders, dataset_sizes, class_names = setup_data(data_dir, batch_size)
    num_classes = len(class_names)
    print(f"检测到 {num_classes} 个类别: {class_names}")

    # 构建模型
    model = setup_model(num_classes)

    # 损失函数和优化器
    criterion = nn.CrossEntropyLoss()

    # 对不同层使用不同的学习率
    # 新添加的层使用较高学习率，预训练层使用较低学习率
    optimizer = optim.AdamW([
        {'params': model.fc.parameters(), 'lr': 0.001},         # 最后一层使用较高学习率
        {'params': list(model.parameters())[:-2], 'lr': 0.0001} # 其他层使用较低学习率
    ], weight_decay=0.01)  # AdamW优化器自带权重衰减正则化

    # 学习率调度器 - 使用余弦退火带重启的学习率策略
    scheduler = lr_scheduler.CosineAnnealingWarmRestarts(
        optimizer, T_0=10, T_mult=1, eta_min=1e-6
    )

    # 开始训练模型
    model = train_model(
        model, dataloaders, dataset_sizes, criterion, optimizer,
        scheduler, work_dir, num_epochs
    )

    # 保存最终模型
    torch.save({
        'model_state_dict': model.state_dict(),
        'optimizer_state_dict': optimizer.state_dict(),
        'class_names': class_names,
    }, os.path.join(work_dir, 'final_model.pth'))

    print(f"模型已保存至 {work_dir}/final_model.pth")
```

4 Experiments



This experiment focused on the application of deep learning techniques for image classification, utilizing a pre-trained ResNet50 architecture fine-tuned to classify images from a flower dataset. The process involved adapting neural network principles taught in class, such as transfer learning, data augmentation, and optimization strategies, to improve model performance.

Key classroom concepts applied included the use of convolutional layers for feature extraction and fully connected layers for classification. We employed transfer learning by leveraging pre-trained weights from the ResNet50 model, which were initially trained on the ImageNet dataset. This allowed us to benefit from the rich feature representations learned from a large dataset, significantly reducing training time and improving accuracy on our specific task.

Data preprocessing was another critical aspect where we applied transformations like random cropping, flipping, and color jittering during training. These steps are essential in simulating variations that the model might encounter in real-world scenarios, thereby enhancing robustness—a concept emphasized in our studies regarding generalization capabilities of neural networks.

The training phase incorporated an advanced optimizer, AdamW, with differential learning rates for various parts of the network. A cosine annealing learning rate scheduler was also implemented to dynamically adjust the learning rate, facilitating better convergence.

Despite achieving a high validation accuracy of 98%, some challenges persisted. The relatively high training loss suggested possible overfitting, indicating that future work should explore additional regularization methods or architectural simplifications to enhance generalization while maintaining high performance.

References

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