Documentation: Experiment-3

By-AMAN

Roll no- 2K22/CO/48

1. Introduction

This project focuses on image classification using Convolutional Neural Networks (CNNs) to classify images from two datasets: **Cats vs. Dogs** and **CIFAR-10**. The implementation involves training custom CNN models, experimenting with different activation functions and weight initializations, and utilizing Transfer Learning with **ResNet-18** for improved performance.

2. Dataset Overview

2.1 Cats vs. Dogs Dataset

- The dataset consists of images of cats and dogs, categorized into two classes.
- Preprocessing steps include:
 - Resizing images to 64×64 pixels.
 - Normalization using mean and standard deviation.
 - Splitting into training (80%) and validation (20%) sets.

2.2 CIFAR-10 Dataset

- Contains 10 object classes, including animals, vehicles, and objects.
- Similar preprocessing steps as Cats vs. Dogs.
- Used as an additional dataset for experimentation.

3. Model Architecture

A **custom CNN model** is implemented with the following structure:

Convolutional layers:

```
Conv2D(3 → 32) → BatchNorm → Activation → MaxPool
Conv2D(32 → 64) → BatchNorm → Activation → MaxPool
```

• Fully Connected Layers:

```
\circ FC (64*16*16 \rightarrow 512) \rightarrow Dropout \rightarrow Activation \circ FC (512 \rightarrow Output Classes)
```

 Supports different activation functions (ReLU, Tanh, Leaky ReLU) and weight initialization methods (Xavier, Kaiming, Random).

4. Training Setup

4.1 Training Parameters

• Batch size: 32

Optimizers tested: SGD, Adam, RMSProp
Loss Function: CrossEntropyLoss

• **Epochs**: 10

4.2 Training Process

1. Model is trained on Cats vs. Dogs and CIFAR-10 datasets.

2. Training and validation losses/accuracies are recorded.

3. The best model is selected based on validation accuracy.

5. Transfer Learning with ResNet-18

- A pretrained **ResNet-18** model is fine-tuned for classification.
- The final fully connected layer is modified to classify:
 - 2 classes (Cats vs. Dogs)
 - 10 classes (CIFAR-10)
- Adam optimizer is used for training.
- The trained model weights are saved for inference.

6. Results & Performance Evaluation

- Loss and accuracy curves are plotted for both training and validation phases.
- Comparisons are made between different activation functions, weight initializations, and optimizers.
- ResNet-18 outperforms custom CNN, showing the effectiveness of Transfer Learning.

7. Conclusion

This project demonstrates:

- The impact of different hyperparameters on CNN performance.
- How Transfer Learning can significantly improve classification accuracy.
- The importance of dataset preprocessing and augmentation techniques.

8. Future Enhancements

- Experiment with deeper CNN architectures.
- Implement data augmentation to improve generalization.
- Utilize other pretrained models like VGG-16, EfficientNet, etc.

References

- PyTorch Documentation
- Torchvision Datasets

• Deep Learning Papers on Transfer Learning

Technologies Used: Python, PyTorch, Torchvision, Matplotlib

Github repository link: https://github.com/amank010/Deep-Learning-Lab.git