MACHINE LEARNING

LAB – WEEK 14

PROJECT TITLE: CNN Image classification

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COURSE: Machine Learning

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PROJECT OVERVIEW:

The purpose of this lab is to design, build, and train a Convulution Neural Network using PyTorch. This model must be able to accurately classify images of hand gestures into one of three categories: 'rock', 'paper', or 'scissors'.

MODEL ARCHITECTURE:

The model consists of multiple convolutional layers that progressively extract spatial and textural features from the images:

- Conv Layer 1:

Input channels: 3 (RGB), Output channels: 16, Kernel size: 3×3 which is followed by ReLU and MaxPool

- Conv Layer 2:

Output channels: 32, Kernel size: 3×3which is followed by ReLU and MaxPool

- Conv Layer 3:

Output channels: 64, Kernel size: 3×3 which followed by ReLU and MaxPool.

Max Pooling layers help downsample the feature maps and reduce computation while retaining the important features.

Fully-Connected Classifier: After flattening the final feature maps, the model uses:

- ✓ FC1: Linear layer with 128 neurons + ReLU
- ✓ FC2: Linear layer with 3 output units

The final output goes through a softmax implicitly via the CrossEntropyLoss.

TRAINING AND PERFORMANCE

Training Hyperparameters

- ❖ Optimizer used Adam
- ❖ Loss Function: Cross Entropy Loss
- ❖ Learning Rate: 0.001
- ❖ Batch Size: 32

- Epochs: 10

```
Epoch 1/10, Loss = 0.6363
Epoch 2/10, Loss = 0.1840
Epoch 2/10, Loss = 0.1840
Epoch 3/10, Loss = 0.0961
Epoch 3/10, Loss = 0.0961
Epoch 4/10, Loss = 0.0468
Epoch 4/10, Loss = 0.0468
Epoch 5/10, Loss = 0.0223
Epoch 5/10, Loss = 0.0223
Epoch 6/10, Loss = 0.0107
Epoch 6/10, Loss = 0.0107
Epoch 7/10, Loss = 0.0235
Epoch 7/10, Loss = 0.0235
Epoch 8/10, Loss = 0.0124
Epoch 8/10, Loss = 0.0124
Epoch 9/10, Loss = 0.0049
Epoch 9/10, Loss = 0.0049
Epoch 10/10, Loss = 0.0222
Training complete!
Epoch 10/10, Loss = 0.0222
Training complete!
```

Final Test Accuracy

Your model achieved a test accuracy of 98.17%.

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Test Accuracy: 98.17%
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CONCLUSION AND ANALYSIS

Although the model achieved a high accuracy of 98.17%, there is still room for improvement. Using data augmentation techniques such as random rotations, flips and brightness adjustments can make the model more robust to variations in hand poses. Adding regularization methods like dropout or batch normalization can further reduce overfitting. Finally, experimenting with a slightly deeper CNN or using transfer learning from pretrained models could push the accuracy even closer to 100%.