

# **Week 14: CNN Rock Paper Scissors**

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## **1. Introduction**

The goal of this lab was to build and train a Convolutional Neural Network using PyTorch to classify images of rock, paper, and scissors. The task involved designing the model, training it on labeled images, and evaluating how well it performed on a separate test set.

## **2. Model Architecture**

### **Convolutional Network**

The model uses three convolutional blocks:

- Block 1: Input with 3 channels, 16 filters, kernel size 3, padding 1, ReLU, Max Pooling with size 2
- Block 2: 32 filters, kernel size 3, padding 1, ReLU, Max Pooling with size 2
- Block 3: 64 filters, kernel size 3, padding 1, ReLU, Max Pooling with size 2

After these steps, an input image of size 128 by 128 is reduced to a feature map of size 16 by 16 with 64 channels. This results in 16384 features once flattened.

### **Classifier**

The flattened tensor is passed into a linear layer that reduces 16384 features to 256. ReLU is applied, followed by dropout with probability 0.3. A final linear layer maps the 256 features to 3 output classes.

## **3. Training and Performance**

Training used the Adam optimizer with a learning rate of 0.001. The loss function was CrossEntropyLoss. The batch size was 32 and the model trained for 10 epochs.

The loss decreased consistently across epochs, moving from 0.6251 in the first epoch to 0.0247 in the tenth. On a test set of 438 images, the final accuracy reached 98.17%

```
Epoch 1/10, Loss = 0.6251
Epoch 2/10, Loss = 0.1919
Epoch 3/10, Loss = 0.0894
Epoch 4/10, Loss = 0.0515
Epoch 5/10, Loss = 0.0431
Epoch 6/10, Loss = 0.0186
Epoch 7/10, Loss = 0.0111
Epoch 8/10, Loss = 0.0080
Epoch 9/10, Loss = 0.0410
Epoch 10/10, Loss = 0.0247
Training complete!
```

## 4. Conclusion and Analysis

The model performed very well and achieved high accuracy on unseen images. The use of three convolutional blocks and dropout appears to have supported effective learning without major overfitting.

Randomly selected images:

Image 1: </content/dataset/scissors/sJtSZbQH0MF9U4oa.png>

Image 2: </content/dataset/paper/mZW0RUegJ19SM8ck.png>

Player 1 shows: scissors

Player 2 shows: paper

RESULT: Player 1 wins! scissors beats paper

Challenges included keeping track of shape changes after pooling layers and ensuring that tensors were placed on the correct device during training.

Accuracy could potentially be improved by adding data augmentation, such as rotations or flips, or by introducing batch normalization. Trying additional convolutional layers or using a learning rate schedule may also be helpful in future experiments.