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Assignment: Assignment 2 – CNN Implementation from Scratch

1. Introduction

Brief overview of the assignment goals.

This project involved implementing a complete Convolutional Neural Network (CNN) framework from scratch in Python, without using any deep learning libraries such as PyTorch or TensorFlow. The implementation covers core CNN components, a custom training loop, and evaluation metrics, all designed to be modular and extensible.

2. Design and Architecture

2.1 Layer System

Each layer (Conv2D, ReLU, Pooling, etc.) is implemented as a class with forward() and backward() methods, conforming to a base Layer interface for modularity.

2.2 Model Pipeline

A custom Model class manages the forward and backward propagation across layers, and supports training with user-defined loss functions and optimizers.

2.3 Optimizations

- im2col for fast convolution
- Xavier initialization
- Support for SGD, Momentum, and Adam
- Dropout and Batch Normalization
- Regularization (L1, L2, Elastic Net)

3. Implemented Features

Feature Description

Conv2D Custom 2D convolution using im2col

MaxPooling Downsampling layer

Flatten Transition to FC

FullyConnected Dense layer

Dropout Regularization

BatchNorm Stability and faster training

Regularization L1, L2, Elastic Net

Optimizers SGD, Momentum, Adam

Model Save/Load Save weights using .npz

Metrics Accuracy and confusion matrix

4. Training and Evaluation

4.1 Dataset

Trained and evaluated on **CIFAR-10**, a 10-class image classification dataset (32×32 RGB).

4.2 Model Architecture

```
Input (3x32x32)

\rightarrow Conv2D (3\rightarrow8)

\rightarrow ReLU

\rightarrow MaxPool (2x2)

\rightarrow Flatten

\rightarrow FC (8*16*16 \rightarrow 10)

\rightarrow Softmax (implicitly in MSE + one-hot)
```

4.3 Training Configuration

• **Epochs**: 10

• Batch size: 1 (per sample forward-backward)

• **Optimizer**: SGD (momentum=0.9)

• **Regularization**: Elastic Net (λ=1e-4)

• Loss: MSE

• One-hot encoded labels

4.4 Evaluation Results

• Test Accuracy: 66.93%

• Confusion Matrix (100 batch index out of 1047):

| [[785 | | 37 | 50 | 20 | 3 | 1 | 9 | 8 | 43 | 44] | |
|-------|----|-----|-----|-----|-----|-----|-----|-----|-----|-------|--|
| [| 21 | 867 | 8 | 3 | 2 | 1 | 6 | 2 | 11 | 79] | |
| [| 88 | 14 | 602 | 75 | 25 | 29 | 101 | 28 | 10 | 28] | |
| [| 52 | 23 | 110 | 474 | 19 | 85 | 128 | 33 | 19 | 57] | |
| [| 54 | 4 | 126 | 106 | 385 | 8 | 193 | 75 | 16 | 33] | |
| [| 24 | 14 | 96 | 233 | 20 | 437 | 62 | 53 | 15 | 46] | |
| [| 8 | 14 | 46 | 62 | 3 | 8 | 840 | 5 | 7 | 7] | |
| [| 21 | 13 | 71 | 76 | 15 | 31 | 25 | 702 | 0 | 46] | |
| [107 | | 54 | 15 | 7 | 1 | 2 | 12 | 3 | 758 | 41] | |
| [| 22 | 86 | 6 | 10 | 1 | 1 | 10 | 4 | 17 | 843]] | |

5. Challenges & Solutions

• Challenge: Slow convolution

Solution: Used im2col for efficient matrix-based convolution

• Challenge: Overfitting

Solution: Added Dropout and L2/Elastic Net regularization

• Challenge: Gradient explosion/instability

Solution: Added BatchNorm, careful initialization

6. Conclusion

The project successfully demonstrates a complete deep learning workflow implemented from scratch using only Numpy. All components from low-level layers to optimizers, metrics, and save/load are functional and tested.