NEW YORK INSTITUTE OF TECHNOLOGY

Project Assignment - 1: CIFAR-10 Image Classification with SimCNN and ResNet50

Vedantsinh Mahida (ID: 1324504)

New York Institute of technology

DTSC740, Deep Learning

Instructor: Kiran Balagani

CIFAR-10 Image Classification with SimCNN and ResNet50

Introduction

In this assignment, I implemented two convolutional neural network (CNN) models to classify images in the CIFAR-10 dataset. The first model, **SimCNN**, was built from scratch as a simple CNN model, while the second model utilized **ResNet50**, a deep learning CNN model available in Keras with pretrained weights. The goal was to evaluate and compare the classification accuracies of these two models.

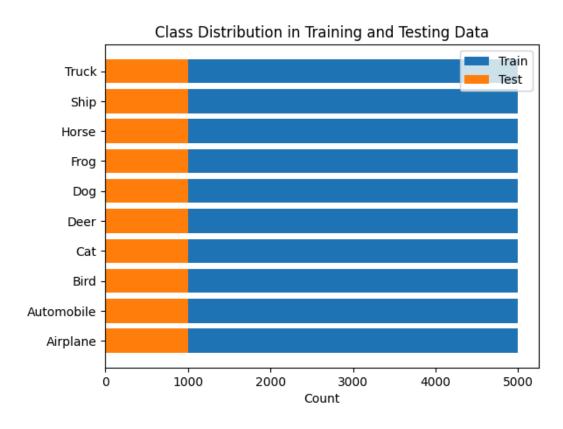
Dataset

The CIFAR-10 dataset consists of 60,000 color images, each of size 32x32 pixels and labeled into one of 10 classes. The dataset is divided into a training set of 50,000 images and a test set of 10,000 images. Below is a preview of the CIFAR-10 dataset.



Class Distribution

During data exploration, a bar graph was created to visualize the class distribution in the CIFAR-10 dataset, showing the number of images per class. This analysis helps ensure that the dataset is balanced across all classes, which is crucial for training an effective model.



Data Specifications

```
(X_train, y_train), (X_test, y_test) = tf.keras.datasets.cifar10.load_data()
print(f"X Train: {X_train.shape}")
print(f"y Train: {y_train.shape}")
print(f"X Test: {X_test.shape}")
print(f"y Test: {X_test.shape}")

X Train: (50000, 32, 32, 3)
y Train: (50000, 1)
X Test: (10000, 32, 32, 3)
y Test: (10000, 32, 32, 3)
```

Model Architectures

SimCNN

The SimCNN model was designed from scratch and includes convolutional layers, batch normalization, max-pooling layers, and fully connected (dense) layers. The architecture of SimCNN is outlined below:

Model: "sequential_2"

| Layer (type) | Output Shape | Param # |
|--|--------------------|---------|
| conv2d_6 (Conv2D) | (None, 30, 30, 32) | 896 |
| batch_normalization_3 (BatchNormalization) | (None, 30, 30, 32) | 128 |
| max_pooling2d_4 (MaxPooling2D) | (None, 15, 15, 32) | 0 |
| conv2d_7 (Conv2D) | (None, 13, 13, 64) | 18,496 |
| batch_normalization_4 (BatchNormalization) | (None, 13, 13, 64) | 256 |
| max_pooling2d_5 (MaxPooling2D) | (None, 6, 6, 64) | 0 |
| conv2d_8 (Conv2D) | (None, 4, 4, 64) | 36,928 |
| batch_normalization_5 (BatchNormalization) | (None, 4, 4, 64) | 256 |
| flatten_2 (Flatten) | (None, 1024) | 0 |
| dense_4 (Dense) | (None, 64) | 65,600 |
| dense_5 (Dense) | (None, 10) | 650 |

Total params: 123,210 (481.29 KB)
Trainable params: 122,890 (480.04 KB)
Non-trainable params: 320 (1.25 KB)

- Layers: Three convolutional layers, each followed by a max-pooling layer. The final layers include a flatten layer, a dense layer with 64 units, and a softmax output layer.
- **Activation Function:** ReLU in hidden layers, softmax in the output layer.

ResNet50

ResNet50 is a pre trained CNN model widely used for image classification tasks due to its deep architecture and residual connections, which help alleviate the vanishing gradient problem. In this project, I used the ResNet50 model with pretrained weights from the ImageNet dataset and fine-tuned it for the CIFAR-10 classification task.

Model: "functional_11"

| Layer (type) | Output Shape | Param # |
|--|---------------------|------------|
| input_layer_1 (InputLayer) | (None, 32, 32, 3) | 0 |
| up_sampling2d (UpSampling2D) | (None, 224, 224, 3) | 0 |
| resnet50 (Functional) | (None, 7, 7, 2048) | 23,587,712 |
| global_average_pooling2d (GlobalAveragePooling2D) | (None, 2048) | 0 |
| flatten_1 (Flatten) | (None, 2048) | 0 |
| dense_2 (Dense) | (None, 1024) | 2,098,176 |
| dense_3 (Dense) | (None, 512) | 524,800 |
| classification (Dense) | (None, 10) | 5,130 |

Total params: 26,215,818 (100.01 MB)
Trainable params: 26,162,698 (99.80 MB)
Non-trainable params: 53,120 (207.50 KB)

Methodology

SimCNN Training:

• Batch Size: 32

• **Epochs**: 20

• Learning Rate: 0.001 (Adam optimizer)

The learning progress was monitored through loss and accuracy metrics over epochs, showing stable convergence.

ResNet50 Training: The ResNet50 model was fine-tuned on the CIFAR-10 dataset, following the original parameter settings outlined in Table 1 and then re-evaluated with modified

parameters. The classification accuracy of the modified ResNet50 was compared with that of the baseline ResNet50 model.

Base Model

```
history = model.fit(
    X_train, y_train, epochs=1, validation_data=(X_test, y_test), batch_size=64)
loss, accuracy = model.evaluate(X_test, y_test, batch_size=64)
```

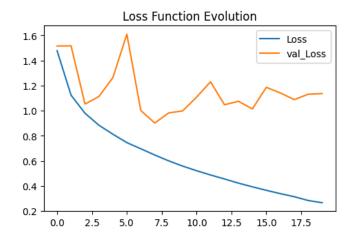
Fine-tuned Model

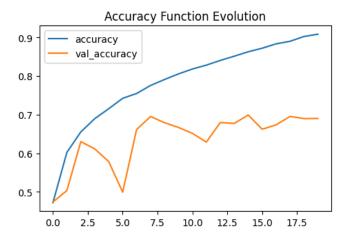
```
his_1 = model.fit(
    X_train, y_train, epochs=1, validation_data=(X_test, y_test), batch_size=32,
)
loss_1, accuracy_1 = model.evaluate(X_test, y_test, batch_size=32)
```

Results

SimCNN Model Performance

SimCNN achieved an accuracy of **90.19**% on the test set, with steady loss and accuracy improvement over epochs. Figures showing the loss and accuracy evolution over epochs were generated.





ResNet50 Model Performance

ResNet50 (Baseline Parameters) achieved a test accuracy of **55.95**%, with some fluctuations likely due to overfitting. After applying custom parameters, the accuracy improved to **89.84**%.

Summary Table of Results

| Model | Parameters | Test Accuracy (%) | Notes |
|-------------------|------------------|-------------------|----------------------|
| SimCNN | Baseline | 90.19 | Stable Performance |
| ResNet50 (Base) | Baseline | 55.95 | Overfitting Observed |
| ResNet50 (Custom) | Paper Parameters | 89.84 | Improvement |

Discussion of Results

- SimCNN: Despite being a simpler model, SimCNN demonstrated stable accuracy and loss convergence, making it suitable for the CIFAR-10 dataset, which is relatively small in terms of image resolution and complexity.
- 2. <u>ResNet50</u>: The ResNet50 model showed lower performance due to overfitting, likely because of the high number of parameters. CIFAR-10's small image size may have limited the benefits of a deeper architecture. Adjusting hyperparameters slightly improved results, though challenges remained due to the dataset's lower resolution.

Conclusion

This assignment provided insights into the performance differences between a custom-built SimCNN model and a pre trained deep learning model, ResNet50, on the CIFAR-10 dataset. Despite its simplicity, SimCNN performed effectively on this task, while ResNet50 faced challenges due to overfitting. Further research and parameter adjustments could improve ResNet50's performance on smaller datasets like CIFAR-10.