CIFAR10

Gwen, Xindi, Olivia, Malka, Salena, Joyce

Table of contents

01. Introduction
Overview

03. Hyper parameters

Describe other hyperparameters

02. Network
Architecture

Describe architecture

04. Model Performance

Loss and accuracy

Table of contents

05. Result Visuals

07. Challenges

The challenges we faced while coding

06. Resolutions

How we solved challenges

08. Conclusion

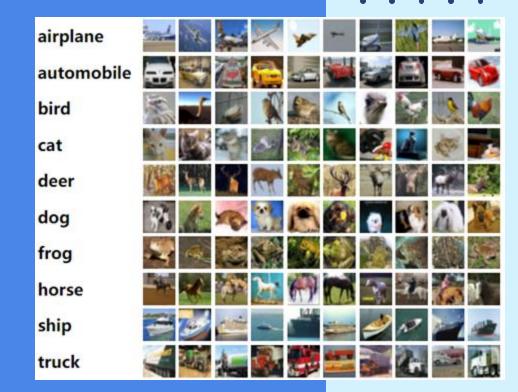
Introduction

CIFAR10:

- 10 different categories
- 60,000 images

Task:

- Create and train a neural network (CNN) for calibrated for accuracy in image classification
 - Image classification:
 - method to classify images into specific categories



ResNet Architecture

Structure:

- Uses ResNet 50 V2
- Multiple dense layers with normalization and dropouts after each one

Theory:

- Multiple convolutional layers
- Skip connections

successful)

- o Prevents explosions and vanishing gradients
- Normalization and dropouts to

prevent overfittii

Total params: 26,159,370

base_model = applications.ResNet50V2(
 weights='imagenet', # Load weights pre-trained on the ImageNet dataset
 input_shape=(224, 224, 3),
 include top=False) # do not include the classifier at the top

```
#build layers
model = models.Sequential([
  layers.Resizing(224, 224),
  layers.RandomFlip("horizontal and vertical"),
  base model.
  layers.Conv2D(128, (3, 3), activation = "relu"),
  layers. Global Average Pooling 2D(),
  layers.Dense(512),
  layers.BatchNormalization().
  layers. Dropout(0.1),
  layers. Activation ("relu").
  layers.Dense(256),
  layers.BatchNormalization(),
  layers.Dropout(0.1),
  layers.Activation("relu"),
  lavers.Dense(128).
  layers.BatchNormalization(),
  layers.Dropout(0.1).
  layers. Activation ("relu").
  layers.Dense(10, activation = "softmax"),
model.layers[2].trainable = False
model.build((None, 32, 32, 3))
```

• • • • •

Network Architecture

Structure:

- Operates in blocks
- Each would convolute, normalize, activate, and use dropout
- Was flattened then put through dense layers

Theory:

- The neurons fan out for convolute and in for dense to preserve the most data possible
- Dropouts after every block to prevent overfitting (partially successful)

```
Conv2D(32, (3, 3), input_shape=(32, 32, 3)),
    BatchNormalization(),
    Activation('relu'),
    Dropout(.05),
    Conv2D(64, (3, 3)),
    BatchNormalization(),
    Activation('relu'),
    Dropout(.1),
    Conv2D(128, (3, 3)),
    BatchNormalization(),
    Activation('relu'),
    Dropout(.1),
    Conv2b(126, (3, 3)),
    BatchNormalization(),
    Activation('relu'),
    Dropout(.1),
    Conv2D(256, (3, 3)),
    BatchNormalization(),
    Activation('relu'),
    Dropout(.1),
    Conv2D(256, (3, 3)),
    BatchNormalization().
    Activation('relu'),
    Dropout(.1),
    Conv2D(512, (3, 3)),
    BatchNormalization(),
    Activation('relu'),
    Flatten(),
    Dense(512),
    BatchNormalization(),
    Activation('relu'),
    Dense(128),
    BatchNormalization(),
    Activation('relu'),
    Dense(10, activation='softmax')
1)
```

#build layers

model = models.Sequential([

Hyperparameters

Optimizer → Adam

Batch_size

ResNet: 128 Fan: 64

Epochs

ResNet: 3 Fan: 30

Workers

Activation → ReLU, Softmax

Model Performance

ResNet

Train acc: 95.59%
Val acc: 89.22%
Test acc:

84.51%

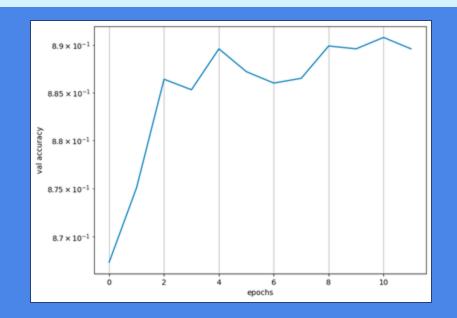
Fan

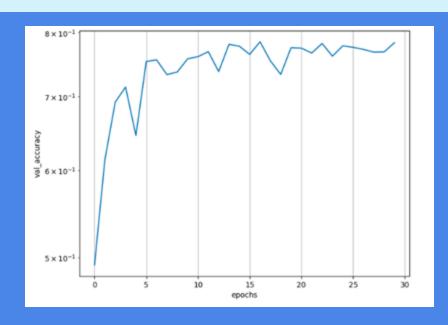
Train acc: Val acc: Test acc: 97.79% 78.04%

76.00%

Progression of Val Accuracy

ResNet Fan Model





Challenges



Problems

- Epoch run time errors
- Overfitting
- Resnet adaptation
- 10% val_accuracy

Solutions

- GP4 and include_top=False
- Regularization
- Checking runtime type
- Fanning in correct direction

Conclusion

ResNet > Fan