

Team:

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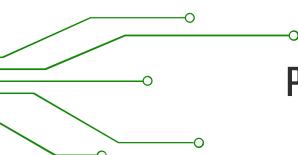
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CLASSIFICATION OF CIFAR-10

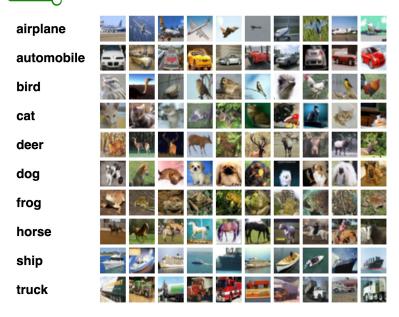
Foundations of Deep Learning 2022/2023

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PURPOSE OF THE PROJECT AND THE DATASET



Purpose of the project: CIFAR-10 dataset is a collection of common images, the model must be able to correctly recognize the type of object or animal represented. Then it has to perform a *classification task*.

The considered dataset is composed by **60000 color images** (32x32, 3 colors RGB) divided in 10 classes (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck). Each image has a single label.

All these classes are mutually exclusive. Each class is formed by 6000 images.

DATA MANAGEMENT AND PRE-PROCESSING

The dataset is composed of:

- 50000 images in the training set;
- 10000 images in the test set.

The test set is divided in:

- 7000 images for the validation set;
- 3000 images for the test set.

Normalization and One-Hot Encoding

- All the pixels of images have values in O-255 range. It's useful, for the efficiency of the model, to normalize these values in O-1 range.
- The labels of images are encoded with One-Hot Encoding.
- Each set of data has the same number of images for each class.



SOLUTION OF THE PROBLEM

For this task a **CNN** has been chosen.



Parameters

- **50** epochs
- Loss = Categorical-Crossentropy
- ReLu and Softmax function
- Different **optimizers**







Three Networks

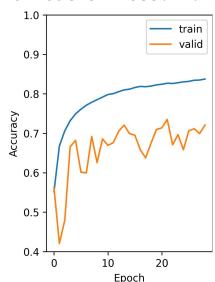
Three different **networks** are developed with different layers and regularizations.

Early stopping is defined with patience = 15 and the loss of the validation set is monitored.

Model 1

Loss: 0.76

Validation Loss: 1.13

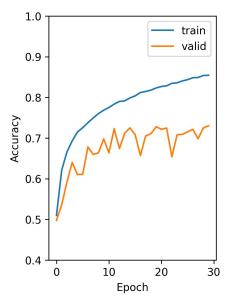


Three Conv2D blocks and two fully connected layers.

Model 2

Loss: 0.42

Validation Loss: 0.89

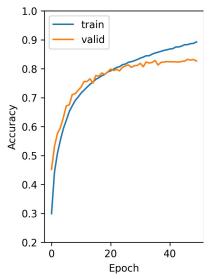


Six coupled Conv2D layers and two fully connected layers.

Model 3

Loss: 0.49

Validation Loss: 0.57



Six coupled Conv2D layers and two fully connected layers

MODEL CHOSEN AND IMPROVEMENTS





Model 3

Optimizer = SGD Weight initializer = he uniform Dropout

Improvements

Data Augmentation Batch Normalization Increasing Dropout More Epochs

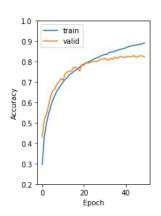
MODEL CHOSEN

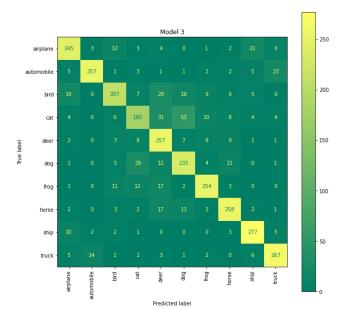


0.49
Train Loss



0.57Validation Loss





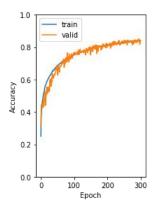
IMPROVEMENTS

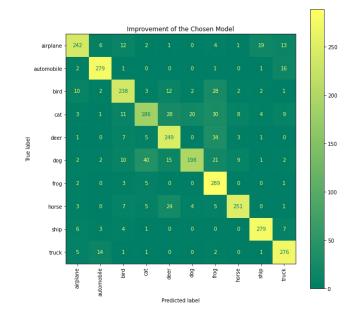


0.46Train Loss

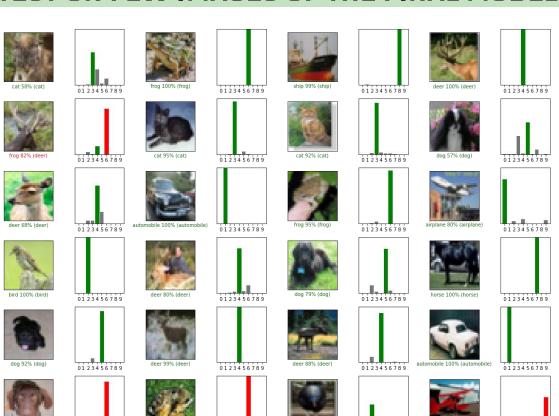


0.48Validation Loss





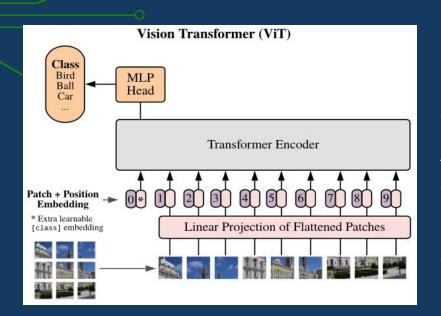
TEST ON FEW IMAGES OF THE FINAL MODEL



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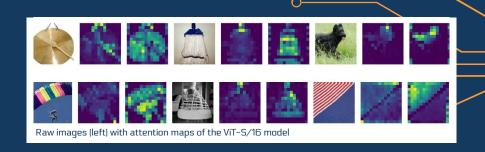
ViT - Vision Transformers



In 2022, the Vision Transformer (ViT) emerged as a competitive alternative to convolutional neural networks (CNNs) that are currently state-of-art in computer vision and therefore widely used in different image recognition tasks.

The ViT is a visual model based on the architecture of a transformer originally designed for text-based tasks. The ViT model represents an input image as a series of image patches (like the series of word embeddings used by transformers for text classification) and it predicts directly class labels for the image.

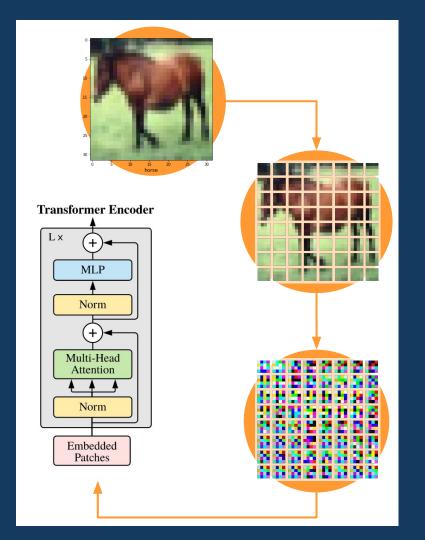
CNN uses pixel arrays, whereas ViT splits the images into visual tokens. The visual transformer divides an image into fixed-size patches, correctly embeds each of them, and includes positional embedding as an input to the transformer encoder.



ViT Architecture

The overall architecture of the vision transformer model is given by following these step-by-step manners:

- Split an image into patches (fixed sizes);
- Flatten the image patches;
- Create lower-dimensional linear embeddings from these flattened image patches (we can think of these now as "tokens");
- Include positional embeddings;
- Feed the sequence as an input to a state-of-art transformer encoder;
- Fine-tune the dataset for **image classification**.



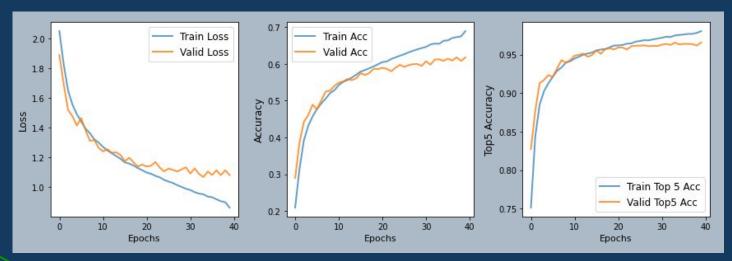
ViT Outcome

Accuracy on the train set of ViT model: 0.69
Accuracy on the validation set of ViT model: 0.62

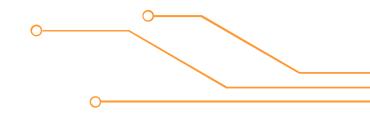
Loss on the train set of ViT model: 0.86

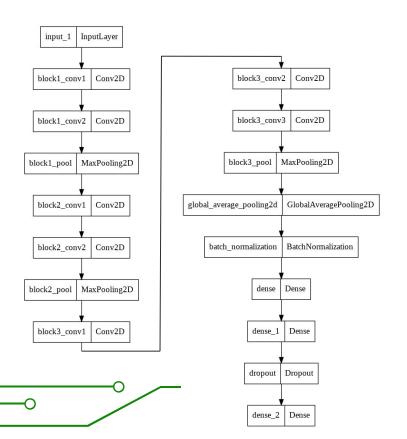
Loss on the validation set of ViT model: 1.08



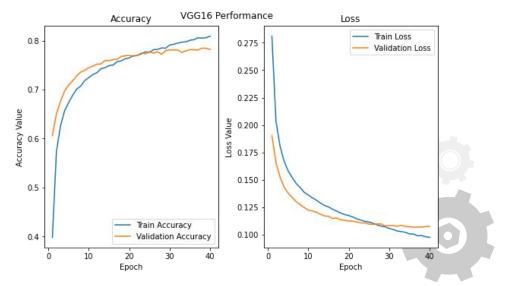


TRANSFER LEARNING: VGG16

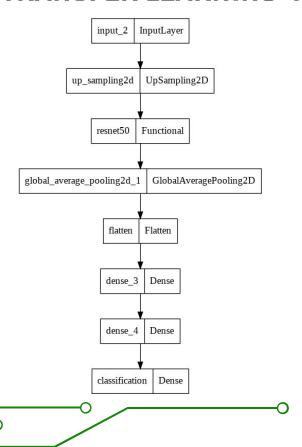




Accuracy on the train set of VGG16: 0.81
Accuracy on the validation set of VGG16: 0.78
Loss on the train set of VGG16: 0.10
Loss on the validation set of VGG16: 0.11

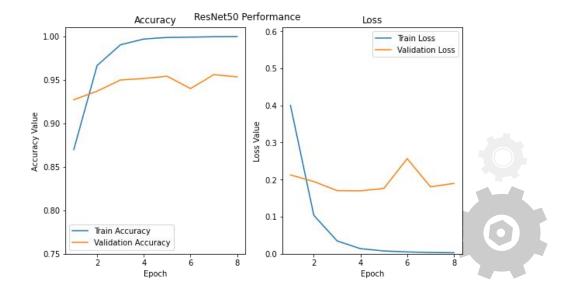


TRANSFER LEARNING: ResNet50



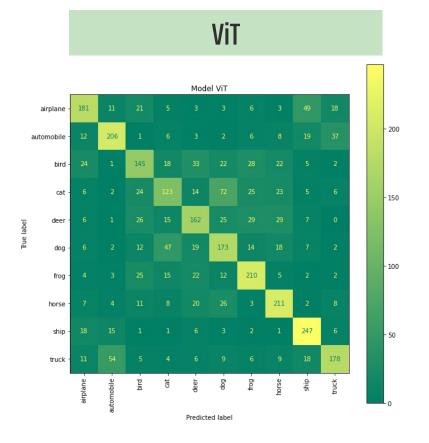
Accuracy on the train set of ResNet50: 0.99
Accuracy on the validation set of ResNet50: 0.95
Loss on the train set of ResNet50: 0.03

Loss on the validation set of ResNet50: 0.20

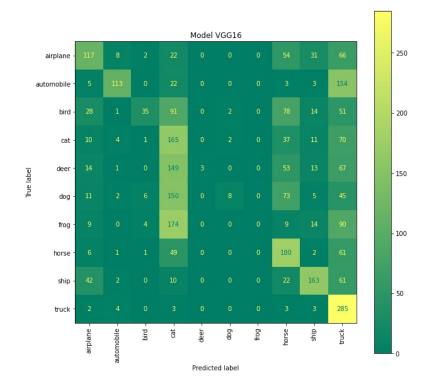




OUTCOME AND FUTURE DEVELOPMENT

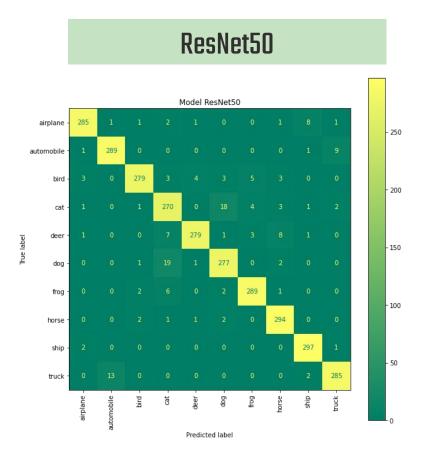


VGG16





OUTCOME AND FUTURE DEVELOPMENT



For the model chosen we suggest to:

- Change learning rates (optimizer);
- → **Resize pixels**, e.q. with standardization;
- Use different regularization techniques (e.q. increase dropout, etc);
- Explore other existing more efficient networks;
- → Try a data ensemble approach;
- → Use PCA to reduce noise in data (as shown in the next slide).

FUTURE DEVELOPMENTS - PCA





29%

Variance captured from the first component.

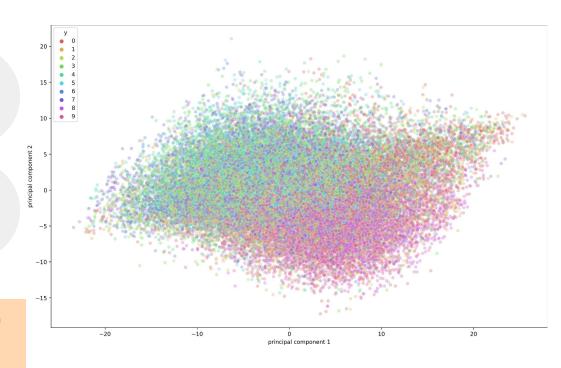


11%

Variance captured from the second component.

Points or images belonging to the same class are <u>closed</u> to each other.

Points or images that are very different semantically are <u>farther</u> from each other.



RESOURCES

RELEVANT WEBSITES:

- <u>datacamp.com/tutorial/principal-component-analysis-in-python</u>
- geeksforgeeks.org/cifar-10-image-classification-in-tensorflow/
- <u>pythonistaplanet.com/cifar-10-image-classification-using-keras/</u>
- machinelearningmastery.com/how-to-develop-a-cnn-from-scratch-for-cifar-10
- kaggle.com/code/faressayah/cifar-10-images-classification-using-cnns-88
- towardsdatascience.com/understand-and-implement-vision-transformer
- viso.ai/vision-transformer-vit/The_vision_transformer_model_uses,processed_by_the_t
 ransformer_encoder
- github.com/sayakpaul/Transfer-Learning-with-CIFAR10/VGG16_Classifier.ipynb
- kaggle.com/resnet50-transfer-learning-cifar-10



Thank you for your attention!