Transfer Learning in Image Classification

Exploring ResNet50 and Custom Model on CIFAR-10 Dataset

[Colaboratory]

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INTRODUCTION

❖ **CIFAR-10 Dataset Overview :**

- 60,000 32x32 color images.
- Represents 10 object classes (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck).
- Collected by Krizhevsky, Nair, and Hinton.
- 50,000 training images, 10,000 test images.
- Widely used for benchmarking image classification algorithms.

❖ **Challenges in Image Classification:**

- Image classification predicts object classes in images (facial recognition, medical imaging).
- Challenges include scale variation, rotation, illumination changes, intra-class variation, occlusions, and background clutter.
- Images have high dimensionality.
- Images have lots of details, making it tough for computers.

Transfer Learning Overview

Transfer learning reuses knowledge from one problem to solve a related one. In deep learning, it means adapting a pre-trained model for a new task.

❖ **Advantages:**

- Reduces the need for large datasets for training.
- Saves time, resources, and costs in training.
- Utilizes existing model's learned features on extensive datasets.
- Achieves high accuracy with smaller specialized datasets.

❖ **Leveraging Pre-trained Models:**

- Models like ResNet, VGG trained on ImageNet provide complex feature representations.
- Customize and retrain higher layers for specific tasks through fine-tuning.

Pre-trained Model – ResNet50

ResNet50 is a super smart computer system with 50 layers, designed to figure out what's in pictures. It won a big competition in 2015 where it had to recognize things in a huge collection of over 14 million pictures.

- Developed for the 2015 ImageNet challenge by Microsoft researchers.
- ResNet50 is excellent because it can handle very complicated details in images.
- Its layers work together - some look at simple things like edges and textures, while others put these details together to recognize complex patterns, like animals, cars, and even really unusual objects.
- ResNet50's knowledge can be used to quickly teach it new things without starting from scratch, which is really helpful for special tasks.
- Excelled in classifying images into diverse categories.

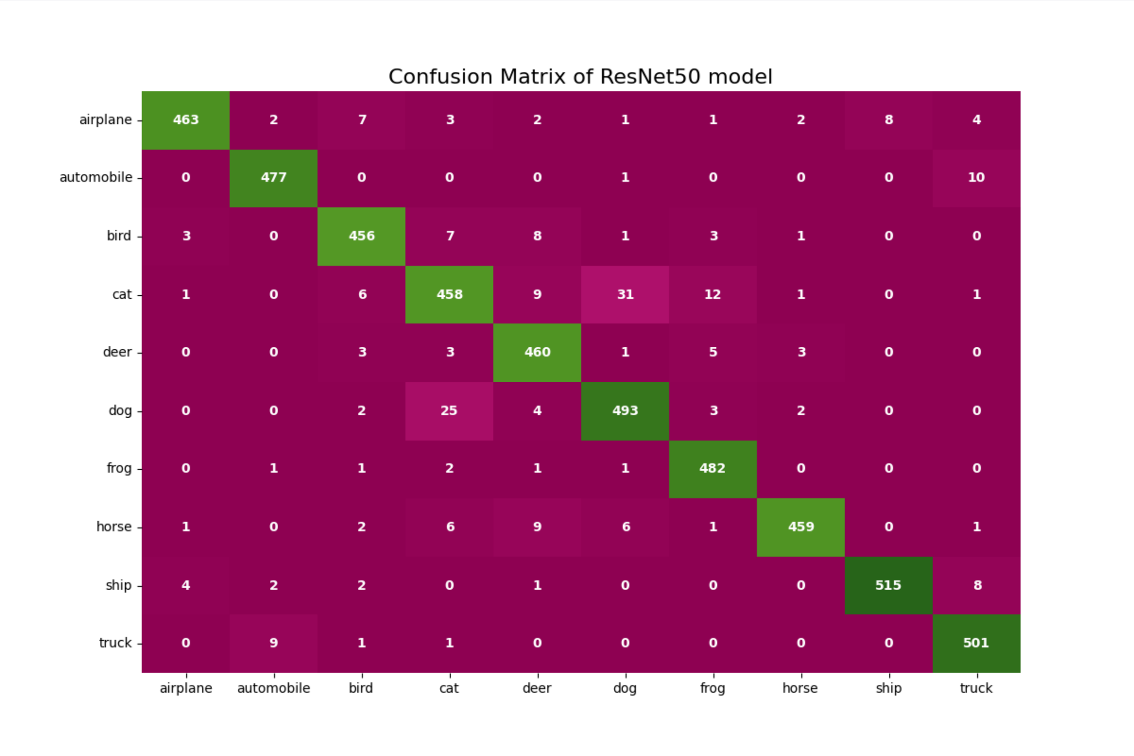
Fine-Tuning

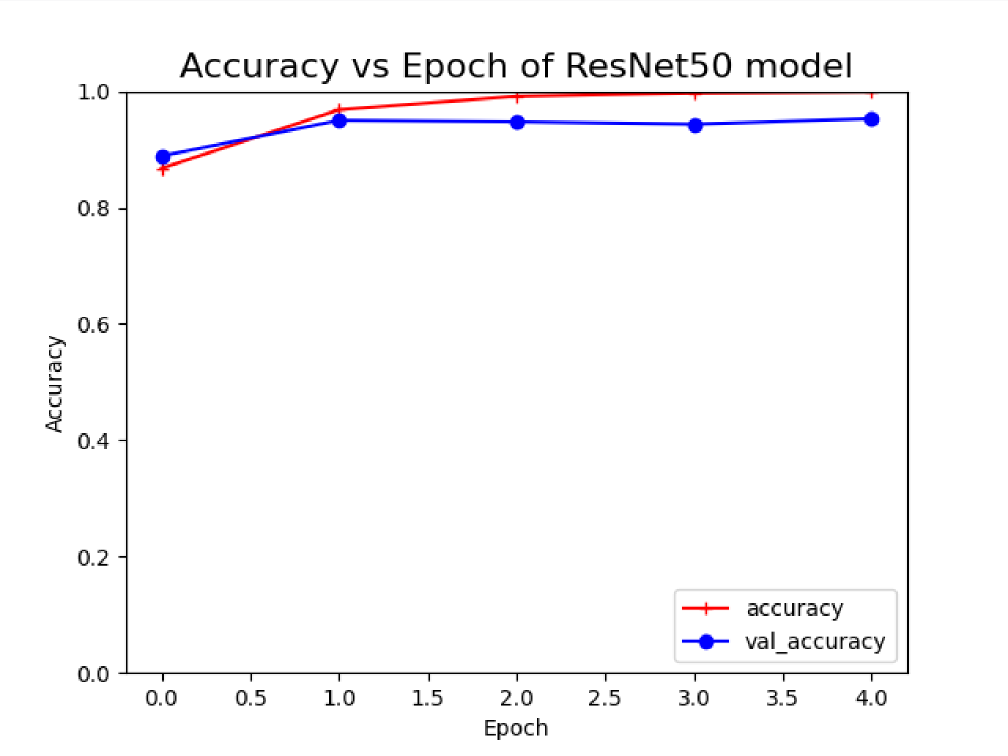
Fine-tuning refers to customizing a pretrained model like ResNet50 for a new task, leveraging its already learned feature representations.

- Froze early ResNet50 layers to retain pre-trained weights.
- Unfroze last few higher layers (from layer 100) for fine-tuning the dataset specific features.
- Used SGD optimizer and default learning rate for SGD, which is typically 0.01.
- Leveraged EarlyStopping and ModelCheckPoint callbacks to prevent overfitting.
- Fit model on train data monitoring loss on validation set.

CIFAR-10 is a dataset with small 32x32 images. Unlike larger datasets, CIFAR-10 may need to capture more detailed and specific features in the images. So, by Unfreezing more layers in the neural network allows the model to learn and adapt to these specific details, enhancing its ability to handle the intricacies of the smaller images in CIFAR-10.

Results - ResNet50





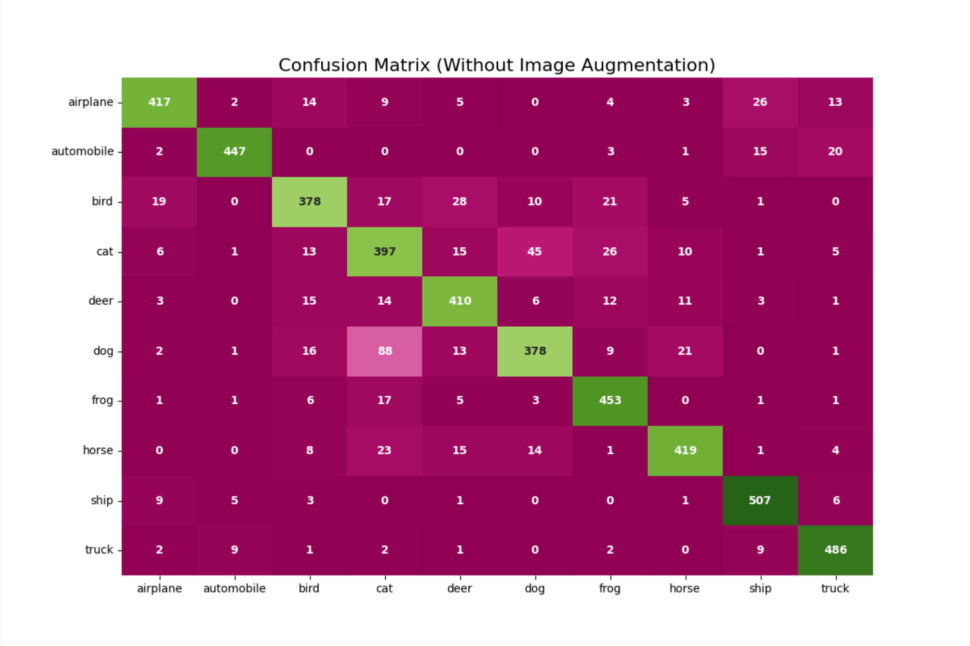
ResNet50 fine-tuning achieves 95% accuracy by epoch 5 indicating effective learning on CIFAR-10.

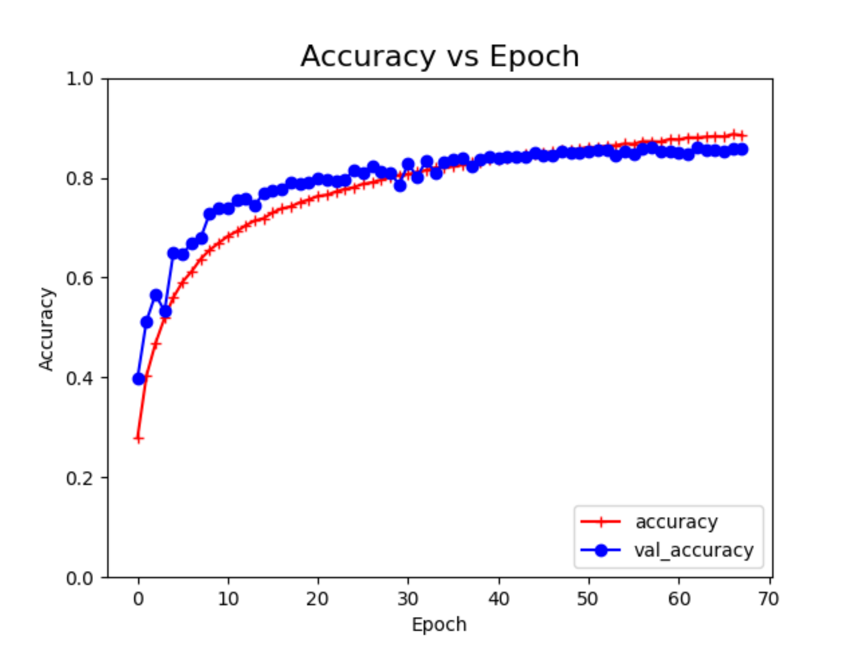
Custom CNN Model

Custom CNN uses typical architecture with convolutional feature extraction, regularization techniques and tuned hyperparameters for CIFAR-10 dataset.

- ➢ Sequential model with 3 sets of convolutional blocks.
- ➢ Conv2D layers - Perform convolutional filtering to extract features.
- ➢ Batch normalization - Regularization, faster convergence.
- ➢ Max pooling - Reduces dimensions to avoid overfitting.
- ➢ Dropout - Randomly drops nodes to avoid overfitting.

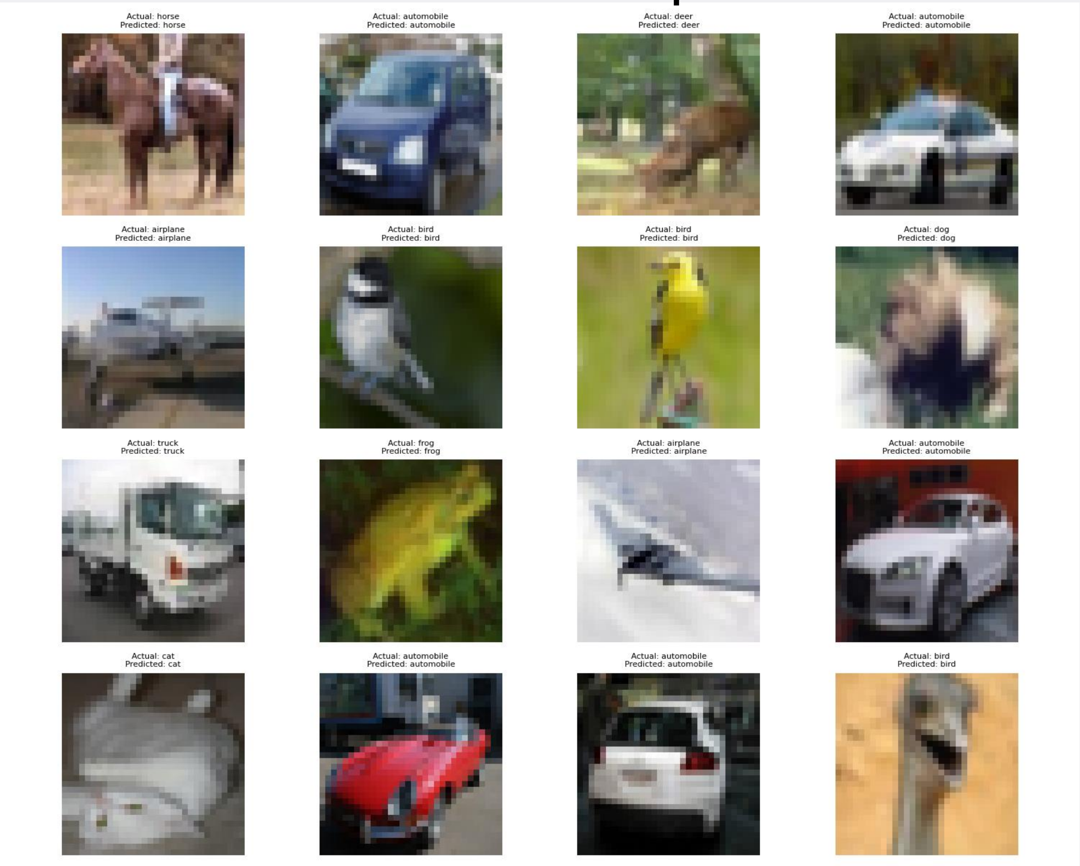
Custom CNN achieves 86% accuracy by epoch 68 on CIFAR-10.



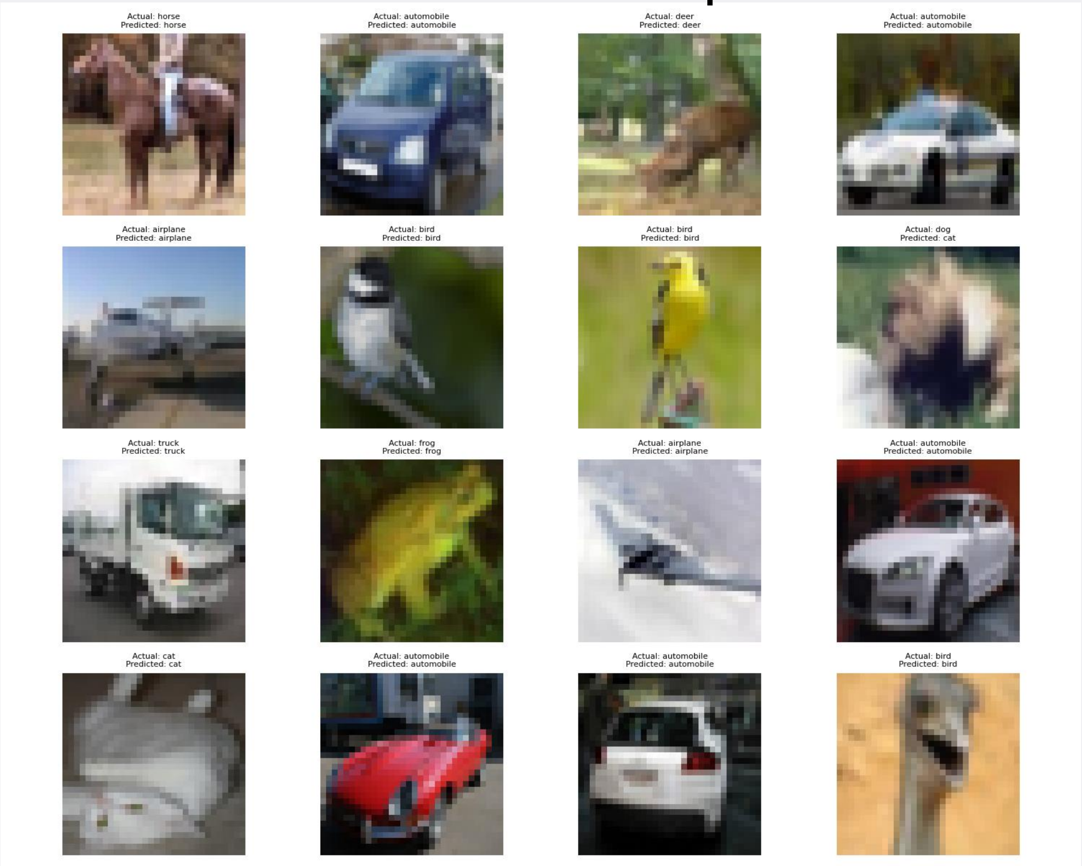


Sample Test Images Comparison

ResNet50 Model Sample



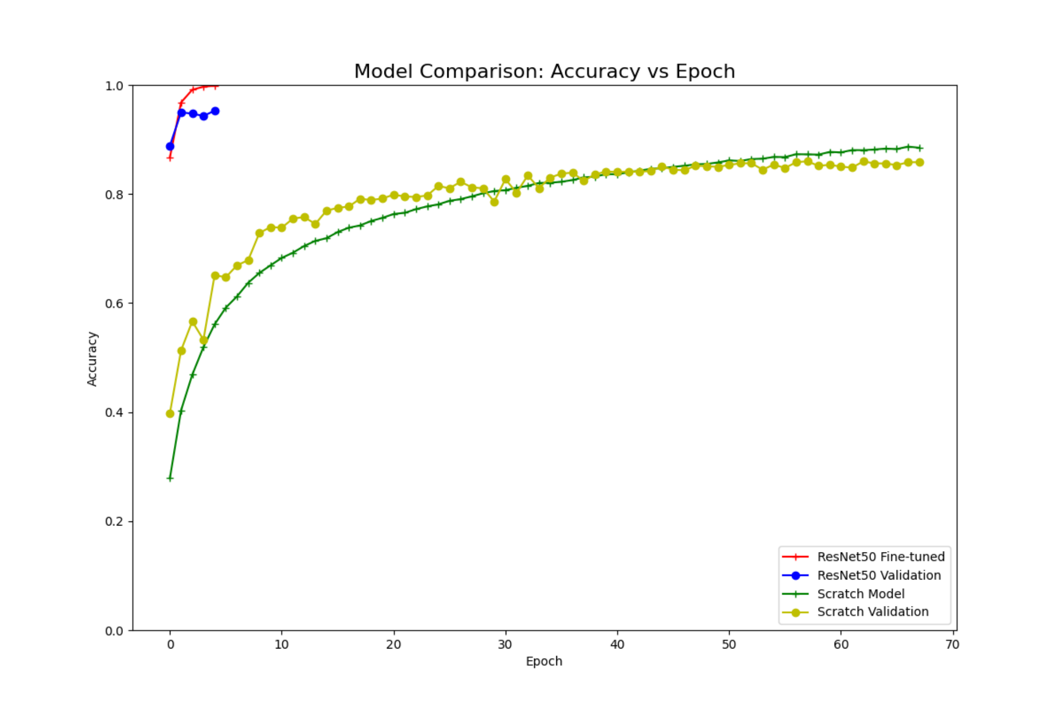
Custom CNN Model Sample



In this comparison of 16 sample test images, it's evident that ResNet50 achieved flawless predictions, correctly identifying all objects. Meanwhile, our Custom CNN Model, while performing exceptionally well, had one misclassification. This underscores the robustness of ResNet50 in capturing intricate patterns

Comparison and Conclusion

- ResNet50 achieves higher accuracy of 95% vs 86% for custom CNN.
- Training from scratch takes more epochs and longer time.
- Training ResNet50 takes fewer epochs and less time due to leveraging pre-trained weights, resulting in faster convergence.
- Transfer learning efficient way to boost accuracy with small data.
- The custom CNN holds potential for better performance with more data and parameter tuning.



Reference

Aguas, K.C. (2020). A guide to transfer learning with Keras using ResNet50. [online] Medium. Available at: https://medium.com/@kenneth.ca95/a-guide-to-transfer-learning-with-keras-using-resnet50-a81a4a28084b.

ResearchGate. (n.d.). (PDF) A Study on CNN Transfer Learning for Image Classification. [online] Available at: https://www.researchgate.net/publication/325803364_A_Study_on_CNN_Transfer_Learning_for_Image_Classification.