Xception: Deep Learning with Depthwise Separable Convolutions

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Overview

Introduction

Introduction and Motivation

Convolutional layers in CNNs typically learn spatial and cross-channel correlations **jointly**, leading to:

- High computational cost
- Large number of parameters

Inception modules improved efficiency by:

- Using 1×1 convolutions for channel mixing
- Followed by 3×3 or 5×5 convolutions for spatial filtering

Xception takes this idea to the extreme:

- **Depthwise convolution:** spatial filtering per channel
- **Pointwise convolution:** mixes channel-wise information
- *Fully decouples spatial and cross-channel learning*

Result: A simpler, more efficient architecture that outperforms Inception V3 with similar parameter count.

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Inception model

Inception vs. Depthwise Separable Conv

- Inception: Partial separation of concerns.
- Depthwise Separable Convolution:
  1. Depthwise convolution: spatial filtering, per channel.
  2. Pointwise (1x1) convolution: cross-channel mixing.
- Xception = Extreme version of Inception.

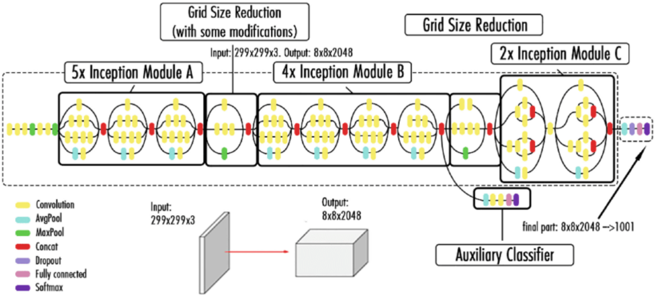


Figure: Inception V3 (source)

Architecture overview

Entry Flow

- Processes raw input and reduces spatial dimensions while increasing depth.
- Two standard `Conv2D` layers:
  - Followed by `ReLU` and BatchNorm
- Three modules, each containing:
  - Two or three `SeparableConv2D` layers
  - Residual shortcut (with 1×1 Conv if needed)
  - `MaxPooling2D` for downsampling

Middle Flow

- Core feature extractor, repeated 8 times
- Each module:
  - Three `SeparableConv2D` layers
  - Each followed by `ReLU` and BatchNorm
  - Ends with a residual connection
- **No change** in feature map size or depth
- Acts as a deep tower for high-level feature extraction

Exit Flow

- Final transformation before classification
- Two `SeparableConv2D` layers + BatchNorm + `ReLU`
- Residual connection (may include 1×1 Conv)
- Final `SeparableConv2D`, followed by:
  - Global Average Pooling
  - Fully-connected or logistic regression layer
- **For ImageNet:** Softmax over 1000 classes

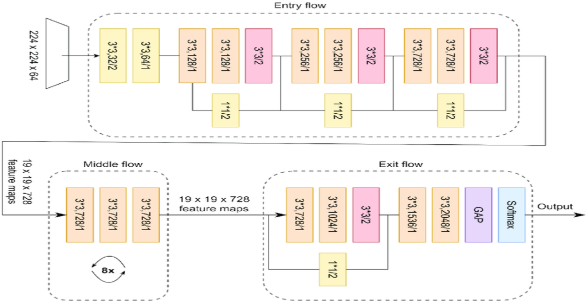


Figure: Xception Architecture (source)

Separable convolution

Depthwise Separable Convolution

- Depthwise: One filter per input channel.
- Pointwise: 1x1 convolution combines channels.
- Much fewer parameters than regular Conv2D.

  Standard Conv: $D_k \cdot D_k \cdot M \cdot N$ Separable Conv: $D_k \cdot D_k \cdot M + M \cdot N$

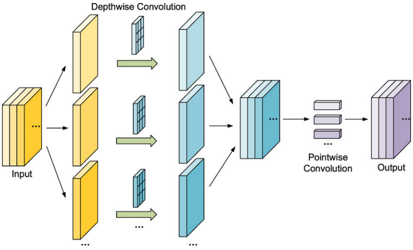


Figure: Depthwise separable convolution (source)

Non-linearity Effects

- ReLU/ELU between depthwise and pointwise layers were tested.
- Result: Omitting the non-linearity improves performance.
- Explanation: Non-linearity may harm shallow (1-channel) intermediate spaces.

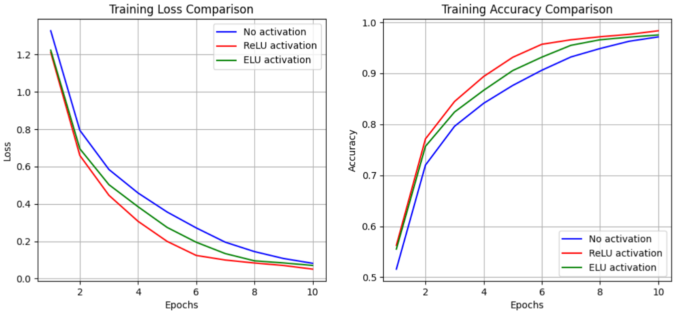


Figure: Effect of non-linearity

Training and evaluation

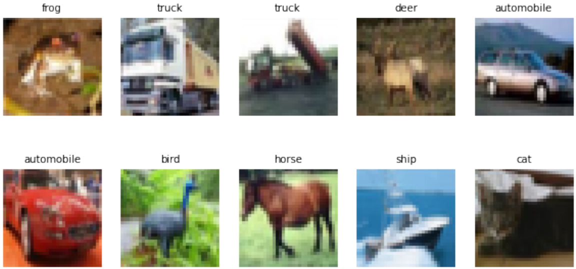
Dataset

Datasets: CIFAR-10 Overview

- **Dataset:** 60,000 color images of size $32 \times 32 \times 3$ (RGB).
- **Classes:** 10 categories (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck).
- **Split:** 45,000 training images, 5,000 validation images and 10,000 test images.
- **Use:** Standard benchmark for image classification, data augmentation, and deep learning methods.

Training setup:

- Adam, GradScaler for dynamic gradient scaling



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CIFAR-10 Preprocessing Overview

- **Training set:**
  - Resize to 320×320, then **random crop** 299×299
  - **Random horizontal flip** (p=0.5) for augmentation
  - Convert to tensor, scale to [0, 1]
  - Normalize using ImageNet stats:
    $\mu = (0.485, 0.456, 0.406), \quad \sigma = (0.229, 0.224, 0.225)$
- **Validation / Test sets:**
  - Resize to 299×299 and **center crop**
  - Tensor conversion + same normalization
- **Split:** 45k train, 5k val, 10k test
- **Batch size:** 128 (DataLoader with shuffle for train, fixed order for val/test)

Comparison with Inception

Performance Comparison

- **Model Size:** Inception V3 is slightly larger with 24.3M parameters compared to Xception's 20.8M, which is about 17% more.
- **Accuracy:** Inception V3 achieves an accuracy of 85.44%, outperforming Xception's 84.87%. This is a gain of $+0.57\%$ with a 17% increase in parameters.
- **Efficiency (Accuracy per million parameters):**
  - Inception V3 $\rightarrow \frac{85.44}{24.3} \approx 3.52\%$ per million parameters
  - Xception $\rightarrow \frac{84.87}{20.8} \approx 4.08\%$ per million parameters

  Xception is more parameter-efficient, but Inception V3 provides higher absolute performance.

Model/performances	**Parameters**	**Accuracy**	**Running time (s)**
Inception V3	$24,371,444$	85.44%	1902.98
Xception	$20,825,402$	84.87%	3116.90

Table: Performance Comparison

The difference in running time simply comes from the fact that Inception model was loaded using pytorch API.

Training curves

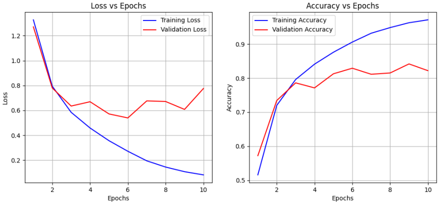

Figure: Training Xception

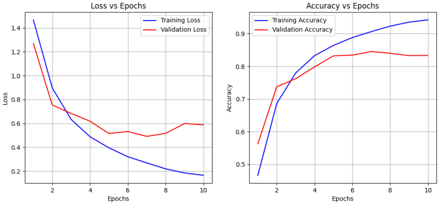

Figure: Training Inception V3

Training curves

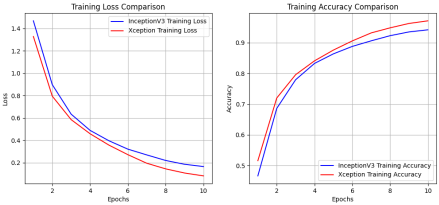

Figure: Inception V3 vs Xception

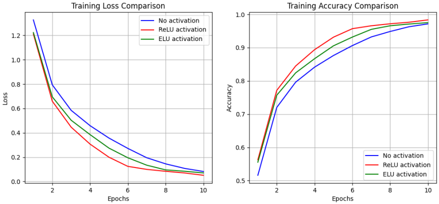

Figure: Xception with different activations

Conclusion

Conclusion

- Xception is a simple, scalable CNN architecture.
- Replaces Inception modules with depthwise separable convolutions.
- Outperforms Inception V3 on both ImageNet and JFT at equal parameter cost.
- Easy to implement and tune with modern frameworks.

The implementation can be found here.
The full article can be found here.

Djeredjef!