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in 2015 to address the vanishing gradient problem in deep neural networks.

The core idea behind ResNet is the use of skip connections, also called residual connections, that allow gradients to flow directly through the network by skipping one or more layers.

This architecture enabled the training of networks with more than 100 layers without performance degradation.

ResNet architectures are typically structured using residual blocks, which consist of convolutional layers followed by batch normalization and ReLU activation.

Each block includes a shortcut connection that adds the input directly to the output of the convolutional layers.

This simple yet powerful innovation became the backbone for many computer vision models, including those used in image classification, object detection, and segmentation.

Variants like ResNet-50, ResNet-101, and ResNet-152 offer different depths.

The ResNet-50 model, for example, uses 50 layers and has become a benchmark for deep learning research.

One of the major strengths of ResNet is its ability to generalize well with fewer training epochs due to improved gradient flow.

Its success on the ImageNet dataset demonstrated its robustness, and it won the 2015 ImageNet Large Scale Visual Recognition Challenge (ILSVRC).

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