PAPER REVIEW

PAPER TITLE

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton

The paper presents *AlexNet*, the first deep CNN proposed to classify large-scale images from the *ImageNet* dataset, encompassing 1.2 million images across 1000 categories. The study highlights the restrictions of traditional machine learning models that depend on handcrafted features, revealing that a deep architecture trained on huge data can attain superior performance. The network consists of five convolutional and three fully connected layers, employing *ReLU activations* for faster learning, *GPU computing* for competent training, and dropout and data augmentation to reduce overfitting. The model accomplished *top 1 and top 5 error rates of 37.5% and 17.0%, respectively*, surpassing earlier approaches by a substantial margin. The findings demonstrated that deep neural networks can automatically learn hierarchical image features when paired with strong hardware and sizable datasets. This marked a significant turning point in computer vision and established the groundwork for further developments in deep learning research.

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The present paper signifies a novel approach in computer vision by representing the influence of training on large datasets using deep convolutional neural networks. It is evident that the beginning of modern deep learning and significant improvement in image classification performance. But one key limitation of the study is its high computational cost and resource dependency, image resizing, heavy dependence on labelled data and inefficiency in deployment. The model needed powerful GPUs and days of training time, which made it difficult for researchers without advanced hardware. Furthermore, the network's substantial number of parameters (around 60 million) made it prone to overfitting and inefficient for deployment on low-power devices.

The above-mentioned limitations can be addressed by emphasising the development of computationally efficient neural network architectures like Mobilenet, ShuffleNet etc., which can achieve similar accuracy with fewer parameters and reduced training time. Besides, cloud-based and distributed computing platforms like Google Colab, TensorFlow Cloud etc. have made high-performance computational resources easily accessible. The extensive training can be minimised by readily available pre-trained models through repositories such as PyTorch Hub and TensorFlow Model Zoo.