Classification (Exellence)

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NAME	SUMMARY	EXELLENCE
AlexNet	AlexNet was one of the pioneering deep convolutional neural networks for image classification. It consists of five convolutional layers and three fully connected layers. It introduced the use of ReLU activation functions and dropout.	AlexNet was known for its breakthrough in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) by significantly reducing error rates in image classification tasks.
ConvNeXt	ConvNeXt is designed to capture multi-scale features by using grouped convolutions. It combines the strengths of both traditional convolutional networks and depthwise separable convolutions.	ConvNeXt aims to excel in image classification tasks and multi-scale feature extraction.
DenseNet	DenseNet uses a unique architecture where each layer is connected to every other layer in a dense manner. It promotes feature reuse and reduces the vanishing gradient problem.	DenseNet excels in image classification tasks and is known for its efficiency in parameter usage.
EfficientNet	EfficientNet is a family of models that optimize network depth, width, and resolution simultaneously. It uses compound scaling to achieve a good trade-off between accuracy and model size. .	EfficientNet is known for its efficiency in terms of computational resources and has achieved state-of-the-art results in various computer vision tasks.

GoogLeNet	GoogLeNet introduced the Inception architecture, which uses multiple filters of different sizes in parallel to capture features at various scales. It helps reduce the number of parameters while maintaining performance.	GoogLeNet is known for its efficiency and excellent performance in image classification and object recognition tasks.
Inception V3	Inception V3 is an improved version of GoogLeNet. It features better utilization of batch normalization, factorized 7x7 convolutions, and auxiliary classifiers to improve training.	Inception V3 excels in image classification, object detection, and related tasks.
MaxVit	MaxVit is a variant of the Vision Transformer (ViT) that incorporates maximum activations and provides a different approach to visual feature learning in transformers.	MaxVit aims to excel in image classification and various computer vision tasks with a unique approach to feature extraction.
MNASNet	MNASNet is a mobile-friendly neural architecture search model designed for mobile and embedded devices. It focuses on efficient network design.	MNASNet is known for its efficiency in terms of model size and computational resources, making it suitable for mobile applications.
MobileNet V2	MobileNet V2 is designed for mobile and embedded devices, with a focus on lightweight and efficient feature extraction using depthwise separable convolutions.	MobileNet V2 excels in real-time image classification and object detection on resource-constrained devices.
MobileNet V3	MobileNet V3 is the successor to MobileNet V2, with improvements in terms of efficiency and accuracy. It introduces neural architecture search for better performance.	MobileNet V3 is designed for resource-constrained devices and focuses on efficiency in image classification tasks.
RegNet	RegNet is designed to explore network architectures based on the principles of regularity and simplicity. It uses a systematic approach to network design with different block types.	RegNet aims to excel in image classification, object detection, and other computer vision tasks. It provides a range of model sizes for various applications.
ResNet	ResNet introduced residual connections, which enable the training of very deep neural networks. It has skip connections that mitigate the vanishing gradient problem.	ResNet is known for its performance in image classification, object detection, segmentation, and more. It is widely used as a backbone architecture in various tasks.

ResNeXt	ResNeXt extends the ResNet architecture by introducing a cardinality parameter that controls the number of parallel paths within each residual block.	ResNeXt excels in image classification and provides a balance between model complexity and accuracy.
ShuffleNet V2	ShuffleNet V2 is designed for efficient network architectures by using channel shuffling to reduce computational cost. It incorporates pointwise group convolutions.	ShuffleNet V2 is known for its efficiency and suitability for resource-constrained devices, such as mobile and edge devices.
SqueezeNet	SqueezeNet is designed to be a highly compact neural network with a small model size. It uses fire modules to reduce the number of parameters while maintaining accuracy.	SqueezeNet is known for its compact size and efficiency, making it suitable for deployment on devices with limited computational resources.
SwinTransformer	SwinTransformer is a vision transformer (ViT) architecture that introduces a hierarchical design with shifted windows and token shifts to capture local and global information effectively.	SwinTransformer aims to excel in image classification and a wide range of computer vision tasks, providing an alternative to convolutional neural networks.
VGG	The VGG network has a simple and uniform architecture with a deep stack of small 3x3 convolutional filters and max-pooling layers.	VGG is known for its simplicity and effectiveness in image classification and feature extraction tasks.
VisionTransformer	Vision Transformer (ViT) is a transformer-based architecture designed for image classification and other computer vision tasks. It converts images into sequences of tokens for processing.	ViT has gained popularity in image classification tasks and is being explored for various vision tasks, including object detection and segmentation.
Wide ResNet	Wide ResNet is an extension of the ResNet architecture, focusing on increasing the width of the residual blocks to improve feature representation.	Wide ResNet is known for its enhanced performance in image classification and related tasks by leveraging wider residual blocks.

1. AlexNet: "ImageNet Classification with Deep Convolutional Neural Networks" by Krizhevsky et al.
2. ConvNeXt: ConvNeXt does not have a specific official paper, but you can search for related publications in academic databases.
3. DenseNet: "Densely Connected Convolutional Networks" by Huang et al.
4. EfficientNet: "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks" by Tan et al.
5. efficientNetV2: efficientNetV2 doesn’t have official paper.
6. GoogLeNet: "Going Deeper with Convolutions" by Szegedy et al.
7. Inception V3: "Rethinking the Inception Architecture for Computer Vision" by Szegedy et al.
8. MaxVit: MaxVit doesn’t have official paper.
   MNASNet: "MnasNet: Platform-Aware Neural Architecture Search for Mobile" by Tan et al.
9. MobileNet V2: "MobileNetV2: Inverted Residuals and Linear Bottlenecks" by Sandler et al.
10. MobileNet V3: "Searching for MobileNetV3" by Howard et al.
11. RegNet: "Designing Network Design Spaces" by Radosavovic et al.
12. ResNet: "Deep Residual Learning for Image Recognition" by He et al.
13. ResNeXt: "Aggregated Residual Transformations for Deep Neural Networks" by Xie et al.
14. ShuffleNet V2: "ShuffleNet V2: Practical Guidelines for Efficient CNN Architecture Design" by Ma et al.
15. SqueezeNet: "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size" by Iandola et al.
16. SwinTransformer: "Swin Transformer: Hierarchical Vision Transformer using Shifted Windows" by Liu et al.
17. VGG: "Very Deep Convolutional Networks for Large-Scale Image Recognition" by Simonyan and Zisserman.
18. VisionTransformer: "An Image Is Worth 16x16 Words: Transformers for Image Recognition at Scale" by Dosovitskiy et al.
19. Wide ResNet: "Wide Residual Networks" by Zagoruyko and Komodakis.