**CNN MODEL AFTER 2017**

**RegNet: A Scalable CNN Model by Facebook AI**

RegNet (Regularized Network) is a family of **scalable CNN architectures** introduced by **Facebook AI in 2020**. It was designed to **automate neural network architecture search** and generate models that achieve a balance between **efficiency and accuracy**.

**1. Key Features of RegNet**

✅ **Automated Architecture Search**: Uses **design principles** instead of brute-force search.  
✅ **Scalability**: Can be customized for different computation budgets.  
✅ **High Accuracy with Fewer Parameters**: Outperforms ResNet and EfficientNet in some cases.  
✅ **Two Variants**: **RegNetX** (basic) and **RegNetY** (includes SE blocks for improved performance).

**2. RegNet Architecture**

Instead of manually designing CNN architectures, RegNet follows a **principled approach** using a simple function:

w(n)=a+b×nw(n) = a + b \times nw(n)=a+b×n

where:

* **w(n)** = number of channels at block **n**
* **a** = initial width
* **b** = slope of width increase

Each **RegNet model consists of four stages**, where the **number of channels increases progressively**.

**Comparison of RegNet Models**

| **Model** | **Parameters** | **FLOPs** | **Top-1 Accuracy (ImageNet)** |
| --- | --- | --- | --- |
| RegNetX-200MF | 2.7M | 200M | 69.0% |
| RegNetX-400MF | 5.2M | 400M | 72.1% |
| RegNetX-800MF | 7.3M | 800M | 74.1% |
| RegNetY-16GF | 84M | 16B | 82.9% |

🔹 **RegNetX** is the standard version.  
🔹 **RegNetY** includes **SE (Squeeze-and-Excitation) blocks** for better feature recalibration.

**3. Advantages of RegNet**

✅ **More Efficient than ResNet** (fewer parameters, higher accuracy).  
✅ **Customizable for different hardware constraints** (small models for mobile, large for cloud).  
✅ **Automated architecture design** reduces the need for manual tuning.  
✅ **RegNetY variant improves feature learning** using SE blocks.

**4. Applications of RegNet**

* **Image Classification** (ImageNet, CIFAR-10, COCO)
* **Object Detection** (RegNet backbone used in **Detectron2**)
* **Medical Imaging** (CT, MRI analysis)
* **Real-time AI on Edge Devices** (low-power RegNetX models)

**5. Comparison: RegNet vs Other CNNs**

| **Model** | **Parameters** | **FLOPs** | **ImageNet Accuracy** |
| --- | --- | --- | --- |
| ResNet-50 | 25.6M | 4.1B | 76.6% |
| EfficientNet-B0 | 5.3M | 0.39B | 77.1% |
| RegNetX-800MF | 7.3M | 0.8B | 74.1% |
| RegNetY-16GF | 84M | 16B | 82.9% |

🔹 **RegNetX models** are more **parameter-efficient** than ResNet.  
🔹 **RegNetY models** achieve **higher accuracy** but have more parameters.

**6. Limitations of RegNet**

❌ **Requires architecture search** (not as easy to implement as ResNet).  
❌ **Not widely supported in all frameworks** (compared to ResNet, EfficientNet).  
❌ **Larger models (RegNetY) are computationally expensive**.

**Conclusion**

* RegNet **automates CNN design**, optimizing for efficiency and scalability.
* It is **more efficient than ResNet** and can be tuned for different computational constraints.
* **RegNet is used in Facebook's Detectron2 for object detection**.

**ConvNeXt: A Modernized CNN Architecture (2022)**

* ConvNeXt is a **next-generation CNN model** introduced by **Meta AI (Facebook AI) in 2022**. It is designed to compete with **Vision Transformers (ViTs)** by integrating ideas from **Swin Transformer** while keeping the efficiency of traditional CNNs.

**1. Key Features of ConvNeXt**

* ✅ **Inspired by Transformers**: Uses **Layer Normalization, GELU activation, and large kernels**.  
  ✅ **More Efficient than Vision Transformers**: Achieves **SOTA (State-of-the-Art) accuracy** while being computationally efficient.  
  ✅ **Depthwise Separable Convolutions**: Reduces the number of parameters.  
  ✅ **Better Scaling**: Works well across different model sizes (ConvNeXt-Tiny to ConvNeXt-XL).

**2. ConvNeXt Architecture vs ResNet**

| **Feature** | **ResNet** | **ConvNeXt** |
| --- | --- | --- |
| Normalization | BatchNorm | LayerNorm (pre-normalization) |
| Activation | ReLU | GELU |
| Kernel Size | 3×3 | **7×7** (inspired by Transformers) |
| Downsampling | Max Pool | Conv (stride=2) |
| Fully Connected Layer | Yes | Global Average Pooling |

* 🔹 **ConvNeXt replaces traditional CNN components with Transformer-like improvements** while keeping convolutional operations.

**3. ConvNeXt Model Variants**

* ConvNeXt comes in different sizes, similar to Transformer models:

| **Model** | **Parameters** | **FLOPs** | **Top-1 Accuracy (ImageNet)** |
| --- | --- | --- | --- |
| ConvNeXt-Tiny | 28M | 4.5B | 82.1% |
| ConvNeXt-Small | 50M | 8.7B | 83.1% |
| ConvNeXt-Base | 89M | 15.4B | 83.8% |
| ConvNeXt-Large | 198M | 34.4B | 84.3% |
| ConvNeXt-XL | 350M | 60.9B | 85.8% |

* 🔹 **ConvNeXt-Tiny** is designed for **mobile and edge AI**, while **ConvNeXt-XL** competes with large ViTs.

**4. Advantages of ConvNeXt**

✅ **Achieves transformer-level accuracy** but **more efficient**.  
✅ **Works well on both ImageNet and COCO** (used for object detection).  
✅ **Better scaling** than ResNet and EfficientNet.  
✅ **ConvNeXt-Tiny is lightweight**, suitable for mobile AI.

**5. ConvNeXt vs Vision Transformers**

| **Model** | **Top-1 Accuracy (ImageNet)** | **FLOPs** |
| --- | --- | --- |
| Swin Transformer-L | 86.3% | 44B |
| ConvNeXt-L | 86.6% | 34B |
| ViT-Huge | 88.5% | 100B+ |

🔹 **ConvNeXt is faster and more efficient** than Vision Transformers while keeping high accuracy.

**6. Applications of ConvNeXt**

🔹 **Image Classification** (ImageNet, CIFAR-10).  
🔹 **Object Detection & Segmentation** (COCO dataset).  
🔹 **Medical Imaging (CT, MRI Analysis)**.  
🔹 **Autonomous Vehicles & Robotics**.

**7. Conclusion**

* **ConvNeXt modernizes ResNet** by integrating Transformer-like improvements.
* **Achieves SOTA performance** while being more efficient than ViTs.
* **Scales well** across different sizes (**Tiny, Small, Base, Large, XL**).