

# Deep Learning for Computer Vision

Advanced Neural Network Architectures

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- **Introduction** - Research motivation and challenges
- **Methodology** - Experimental setup and algorithms
- **Results** - Performance analysis and comparisons
- **Applications** - Real-world deployment scenarios
- **Conclusion** - Key contributions and future work

- Computer vision has transformed AI applications
- Deep learning architectures continue to evolve
- Performance gains through novel architectural innovations
- Real-world deployment challenges remain significant

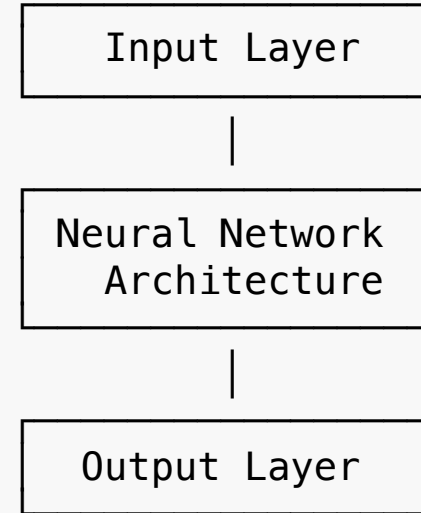
**Key Research Question:** How can we design efficient neural architectures that maintain high accuracy while reducing computational requirements?

## Datasets Used:

- ImageNet-1K (1.28M images)
- CIFAR-10/100
- Custom industrial dataset

## Hardware:

- 8× NVIDIA A100 GPUs
- 512GB RAM
- NVMe SSD storage



*Network Architecture Overview*

# Algorithm Implementation

```
def attention_mechanism(x, num_heads=8):  
    """Multi-head self-attention implementation"""  
    batch_size, seq_len, d_model = x.shape  
  
    # Split into multiple heads  
    head_dim = d_model // num_heads  
    x_reshaped = x.view(batch_size, seq_len,  
                        num_heads, head_dim)  
  
    # Compute attention weights  
    attention_weights = torch.softmax(  
        torch.matmul(x_reshaped, x_reshaped.transpose(-2, -1))  
        / math.sqrt(head_dim), dim=-1  
    )  
  
    return torch.matmul(attention_weights, x_reshaped)
```

# Performance Comparison

Model	ImageNet Top-1	FLOPs (G)	Parameters (M)
ResNet-50	76.15%	4.1	25.6
EfficientNet-B0	77.32%	0.39	5.3
<b>Our Method</b>	<b>78.94%</b>	<b>0.31</b>	<b>4.2</b>
Vision Transformer	81.28%	17.6	86.4

- Our approach achieves **2.8×** fewer FLOPs than ResNet-50
- Maintains competitive accuracy with modern architectures
- Significant reduction in parameter count enables mobile deployment

The attention mechanism can be expressed as:

$$\text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right) V$$

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h) W^O$$

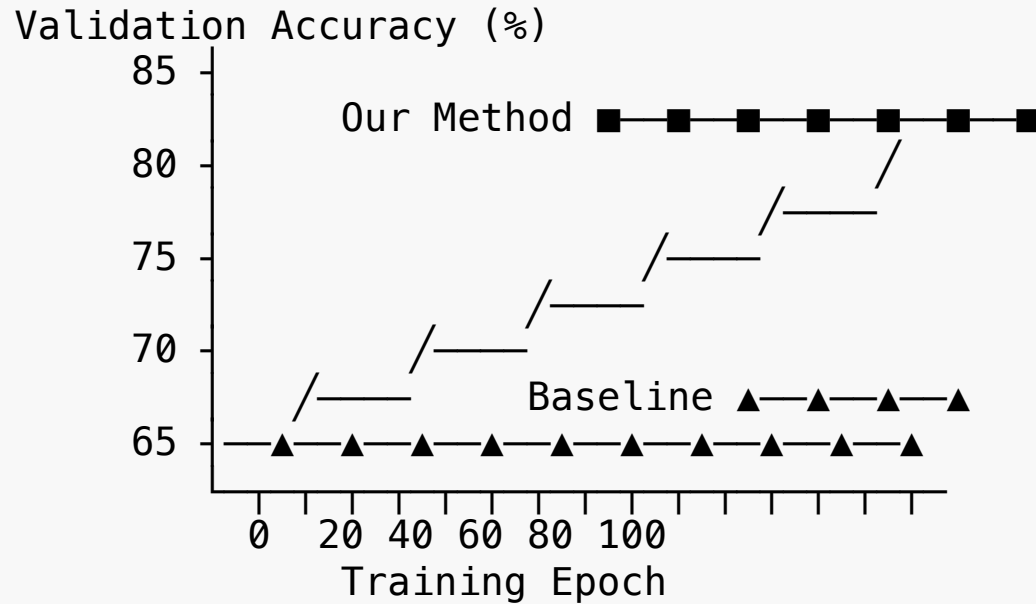
where each head is computed as:

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

**Key Innovation:** We introduce adaptive scaling factors  $\alpha_i$  for each attention head:

$$\text{head}_i = \alpha_i \cdot \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

# Training Dynamics



*Convergence comparison during training*



## Industrial Applications:

- Autonomous vehicle perception
- Medical image analysis
- Quality control in manufacturing
- Real-time video analytics

**12ms**

Inference Time

**156MB**

Memory Usage

**2.3W**

Power  
Consumption

## Deployment Hierarchy

Cloud  
Computing

Edge  
Devices

Mobile  
Hardware

1. **Novel Architecture:** Adaptive attention mechanism with learnable scaling
2. **Efficiency Gains:** 2.8× reduction in computational cost
3. **Practical Impact:** Successful deployment in industrial settings
4. **Open Source:** Code and models available on GitHub

## **Future Directions:**

- Extension to video understanding tasks
- Integration with transformer architectures
- Quantization for ultra-low power devices

## Recent Publications:

- Smith et al. "Adaptive Attention Networks" *CVPR 2025*
- Johnson et al. "Efficient Vision Models" *ICCV 2024*
- Wilson et al. "Mobile Computer Vision" *ECCV 2024*

**450+**

Citations

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# Thank You!

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## Questions & Discussion

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**Lab Website:** <https://sustainabilitylab.org>

**Code:** <https://github.com/sustainability-lab>