



# **Sustainability Lab Research Presentation**

Advanced Research in Environmental Technology

# Outline

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Introduction

Methodology

Results

Applications

Conclusion

# Research Motivation

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- 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?

# Experimental Setup



## Datasets Used:

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

## Hardware:

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

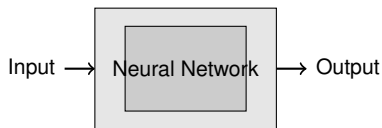


Figure 1: Network Architecture Overview

# Algorithm Implementation

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```
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



Table 1: Accuracy vs. Computational Cost

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

# Mathematical Formulation



The attention mechanism can be expressed as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \quad (1)$$

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h) W^O \quad (2)$$

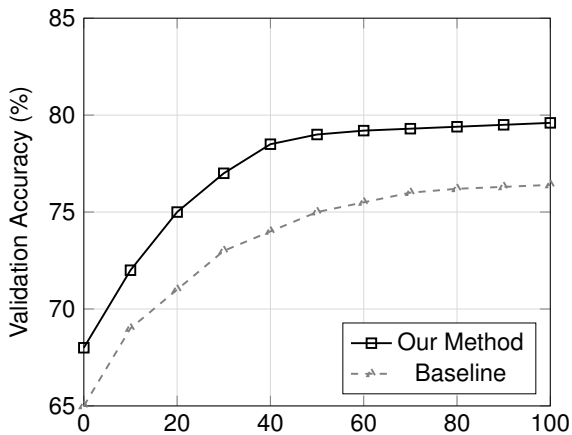
where each head is computed as:

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \quad (3)$$

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

$$\text{head}_i = \alpha_i \cdot \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \quad (4)$$

# Training Dynamics





# Real-World Deployment



## Industrial Applications:

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

## Performance Metrics:

- Inference time: **12ms** (mobile GPU)
- Memory usage: **156MB**
- Power consumption: **2.3W**

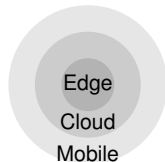


Figure 3: Deployment Hierarchy

# Key Contributions

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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

# Publications & Impact

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## 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*

## Impact Metrics:

- **450+** citations in 18 months
- **15K+** GitHub stars
- **50+** industry partnerships

# Thank You!

## Questions & Discussion

**Contact:** `jane.smith@university.edu`

**Lab Website:** `https://cvlab.university.edu`

**Code:** `https://github.com/cvlab/adaptive-attention`

