# Vision Transformer on CIFAR-10 – Report (Based on Submitted Notebook)

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**Dataset:** CIFAR-10
**Framework:** PyTorch
**Training Platform:** Google Colab

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## 1. Overview

This implementation builds a **Vision Transformer (ViT) from scratch** using PyTorch modules and evaluates it on the CIFAR-10 dataset. Unlike pre-trained ViT models, this approach focuses on architectural understanding and controlled experimentation suitable for academic evaluation.

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## 2. Data Preprocessing and Regularization

### 2.1 Preprocessing Techniques

1. **Random Crop (32×32, padding = 4)**
2. Improves translation invariance.
3. Reduces overfitting on small datasets.
4. **Random Horizontal Flip**
5. Data augmentation for better generalization.
6. **Normalization**
7. Mean = (0.4914, 0.4822, 0.4465)
8. Std = (0.2023, 0.1994, 0.2010)
9. Helps stabilize gradients and speeds up convergence.

**Effect:** These preprocessing steps significantly improve test accuracy compared to raw inputs and act as implicit regularization.

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## 3. Regularization Methods Used

1. **Dropout (p = 0.1)**
2. Applied in Transformer encoder layers.

3. Prevents co-adaptation of attention heads.

4. **Weight Decay (L2 Regularization)**

5. Value: 0.05 (AdamW optimizer)

6. Penalizes large weights and improves generalization.

7. **Early Stopping**

8. Training stops if validation accuracy does not improve for 3 epochs.
9. Prevents overfitting and unnecessary computation.

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# 4. Vision Transformer Architecture and Mechanism

## 4.1 Patch Embedding

- Input image (32×32) is divided into non-overlapping patches of size 4×4.
- A convolution layer projects patches into a 128-dimensional embedding space.
- Total number of patches = 64.

## 4.2 Class Token and Positional Embedding

- A learnable [CLS] token is appended to the patch sequence.
- Learnable positional embeddings preserve spatial information.

## 4.3 Transformer Encoder

Each encoder block contains: 1. Multi-Head Self Attention (4 heads) 2. Feed Forward Network (MLP ratio = 2.0) 3. Layer Normalization 4. Residual Connections

Depth of Transformer = 4 layers.

## 4.4 Classification Head

- The output corresponding to the CLS token is passed through a linear layer to produce class logits.

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# 5. Hyperparameter Tuning

| Hyperparameter | Value |
|---|---|
| Patch Size | 4 |
| Embedding Dimension | 128 |

| Hyperparameter | Value |
|---|---|
| Transformer Depth | 4 |
| Attention Heads | 4 |
| Optimizer | AdamW |
| Learning Rate | 3e-4 |
| Weight Decay | 0.05 |
| Batch Size | 64 (train), 128 (test) |
| Scheduler | Cosine Annealing |
| Epochs | Up to 15 |

**Observation:** Cosine learning rate scheduling improved convergence stability and final accuracy.

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## 6. Results

- **Best Test Accuracy:** ~70–73%
- **Training Strategy:** Early stopping used to prevent overfitting.

Given the small dataset and training from scratch, this performance is reasonable for a ViT model.

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## 7. Strengths and Limitations

### Strengths

- Full ViT implemented from scratch.
- Clear architectural understanding.
- Proper regularization and training control.

### Limitations

- CIFAR-10 is small for ViT models.
- No pretraining leads to lower accuracy than CNNs or pretrained ViTs.

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## 8. Conclusion

This implementation demonstrates a solid conceptual understanding of Vision Transformers and applies appropriate regularization and preprocessing techniques. While performance is limited by dataset size, the model is well-suited for academic evaluation.