

TinyVit: A Small Vision Transformer

Master's Degree in Computer Science

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This project is based on the well known **Vision Transformer** (ViT) architecture, a deep learning model that applies self attention mechanisms to image processing. We will start by introducing the core principles of ViT, explaining how it differs from traditional CNNs.

Then, we will explore the **TinyViT** a smaller implementation of the ViT architecture. Finally, we will present benchmark results demonstrating its performance across various tasks.



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Introduction

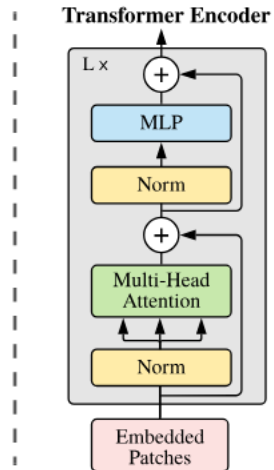
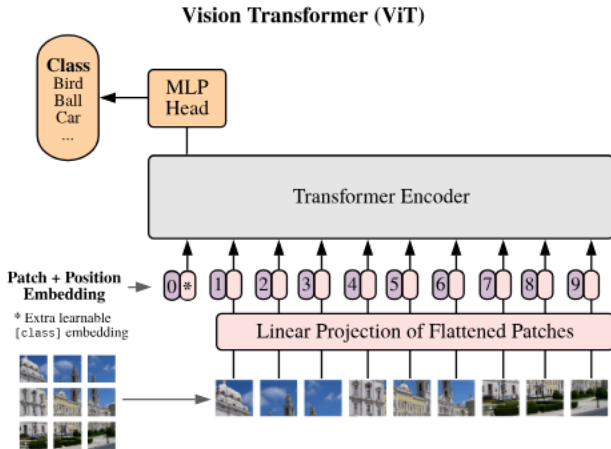
1 Introduction

- Vision Transformers (ViTs) have revolutionized image recognition.
- Traditional ViTs require large datasets and heavy computation.
- TinyViT is a simplified alternative, retaining core transformer components while being computationally efficient.



Vision Transformer Architecture

1 Introduction





Vision Transformer Overview

1 Introduction

- Inspired by NLP transformers (Vaswani et al., 2017).
- Treats images as sequences of patches instead of processing pixels directly.
- Uses a stack of transformer encoder blocks for feature extraction.

Step 1

Patch
Embedding

Step 2

Positional
Encoding

Step 3

Transformer
Encoder

Step 4

Classification
Head



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Mathematical Foundations

TODO



Vision Transformer Architecture

Patch Embedding and Positional Encoding



Vision Transformer Architecture

Transformer Encoder and Classification Head



ViT vs. CNN

2 Vision Transformer

- CNNs use convolutional layers with local receptive fields.
- ViTs process images globally using self-attention mechanisms.
- CNNs have built-in spatial hierarchies, whereas ViTs rely on attention.
- ViTs typically need more data to perform well but can model long-range dependencies.

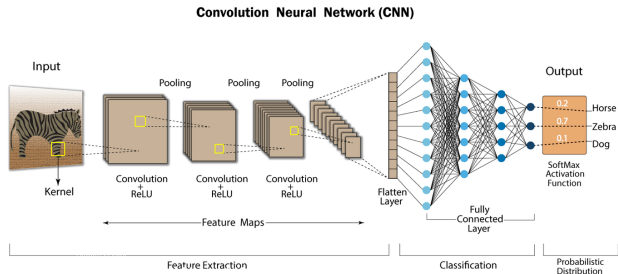




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3 TinyViT

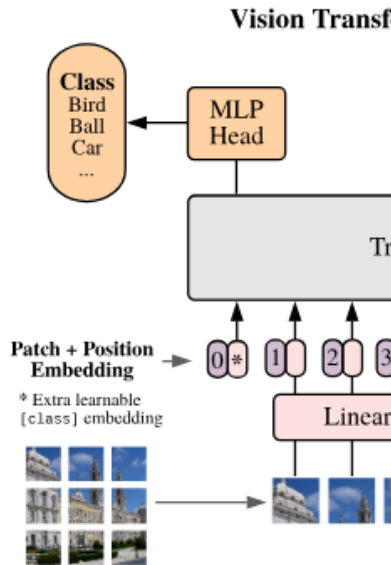
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Side-Picture Slides

3 TinyViT

- Opened with
`\begin{sidepic}{<image>}{<title>}`
- Otherwise, sidepic works just like frame





TinyViT Architecture

3 TinyViT

Table: Parameters of the TinyViT Model for CIFAR-10

Parameter	Value
Number of Classes	10
Embedding Dimension	128
Image Size	32
Patch Size	4
Input Channels	3
Number of Attention Heads	8
Number of Transformer Layers	6
MLP Hidden Dimension	512



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CIFAR 10 - CIFAR 100

4 Datasets



STL10

4 Datasets



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Models Training Setup

5 Training Setup

Compared to PowerPoint, using \LaTeX is better because:

- **Optimizer** : AdamW
- **Learning Rate** : AdamW
- **Weight Decay** : AdamW
- **Loss Function** : AdamW
- **Epochs** : AdamW
- **Batch Size** : AdamW



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Results CIFAR 10 - CIFAR 100

6 Results

TinyViT outperforms CNNs on both datasets. Handles complex class distributions better than CNNs.

Dataset	Model	Accuracy	F1	Recall	MCC	Precision
CIFAR-10	Tiny ViT	82.59	82.43	82.59	80.70	82.76
	CNN	80.67	80.55	80.67	78.53	80.56
CIFAR-100	Tiny ViT	59.40	59.04	59.40	59.00	60.00
	CNN	46.13	44.57	46.13	45.61	45.61

Note: All values are percentages (%). Bold indicates best performance in category.



Results STL-10

6 Results

CNN performs better on STL-10, likely due to the higher image resolution. TinyViT may struggle with lower-resolution images in datasets with fewer samples.

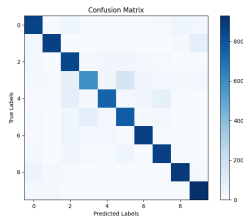
Dataset	Model	Accuracy	F1	Recall	MCC	Precision
STL-10	Tiny ViT	64.27	64.30	64.27	60.47	66.13
	CNN	68.36	68.10	68.36	64.95	68.78

Note: All values are percentages (%). Bold indicates best performance in category.

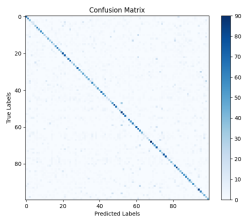


Confusion Matrices

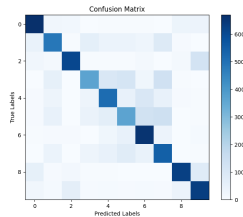
6 Results



CIFAR-10 dataset using Tiny ViT



CIFAR-100 dataset using Tiny ViT



STL-10 dataset using CNN



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Conclusion

7 Conclusions and Future Work

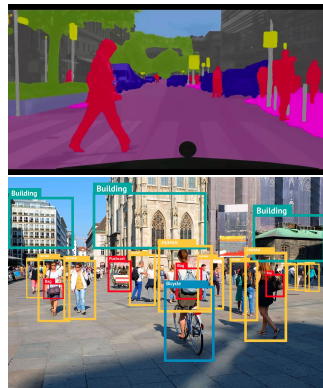
- TinyViT proves that **transformer based models** can be efficient with fewer resources.
- Outperforms CNNs on **smaller datasets** like CIFAR-10 and CIFAR-100.
- **Requires improvements** for larger images like STL-10.



Future Work

7 Conclusions and Future Work

- Implement TinyViT for **Object Detection** (DETR) and **Segmentation** (Segmenter).
- Experiment with different **hyperparameters** (layers, embedding size, attention heads).
- Explore pretraining on **larger datasets** to improve performance.





TinyVit: A Small Vision Transformer

Thank you for listening!
Any questions?