PRUNE AND TELL: VIT VS CONVNEXT IN IMAGE CAPTIONING WITH TOKEN PRUNING

Exploring Efficient Vision-Language Models through Backbone Comparison

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What is image captioning?

"Man in black shirt is playing guitar."

"Construction worker in orange safety vest is working on road."

"Two young girls are playing with lego toy."

Source: COCO captions dataset

- Image captioning is a multimodal problem where the goal is to learn a mapping from visual data (images) to natural language (sentences).

Motivation

Why Efficient Image Captioning or VLM?

- Vision-language tasks (e.g., image captioning, VLM) are computationally expensive.
- Cross attention in image captioning are powerful, but can be redundant in token usage.
- Reducing computation without sacrificing accuracy is crucial for real-time or edge devices.

Theoretical Background

- **Vision Transformer (ViT)**
  Paper: An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale (Dosovitskiy et al., 2020)

- **Swin Transformer**
  Paper: Swin Transformer: Hierarchical Vision Transformer using Shifted Windows (Liu et al., 2021)

- **ConvNeXt**
  Paper: A ConvNet for the 2020s (Liu et al., 2022)

- **MetaFormer**
  Paper: MetaFormer is Actually What You Need for Vision (Yu et al., 2022)

- **Token Pruning**
  - **Paper:** DynamicViT: Efficient Vision Transformers with Dynamic Token Sparsification

Transformer with the multihead self attention is powerfull but redundant in complexity O(n^2)

Image captioning block

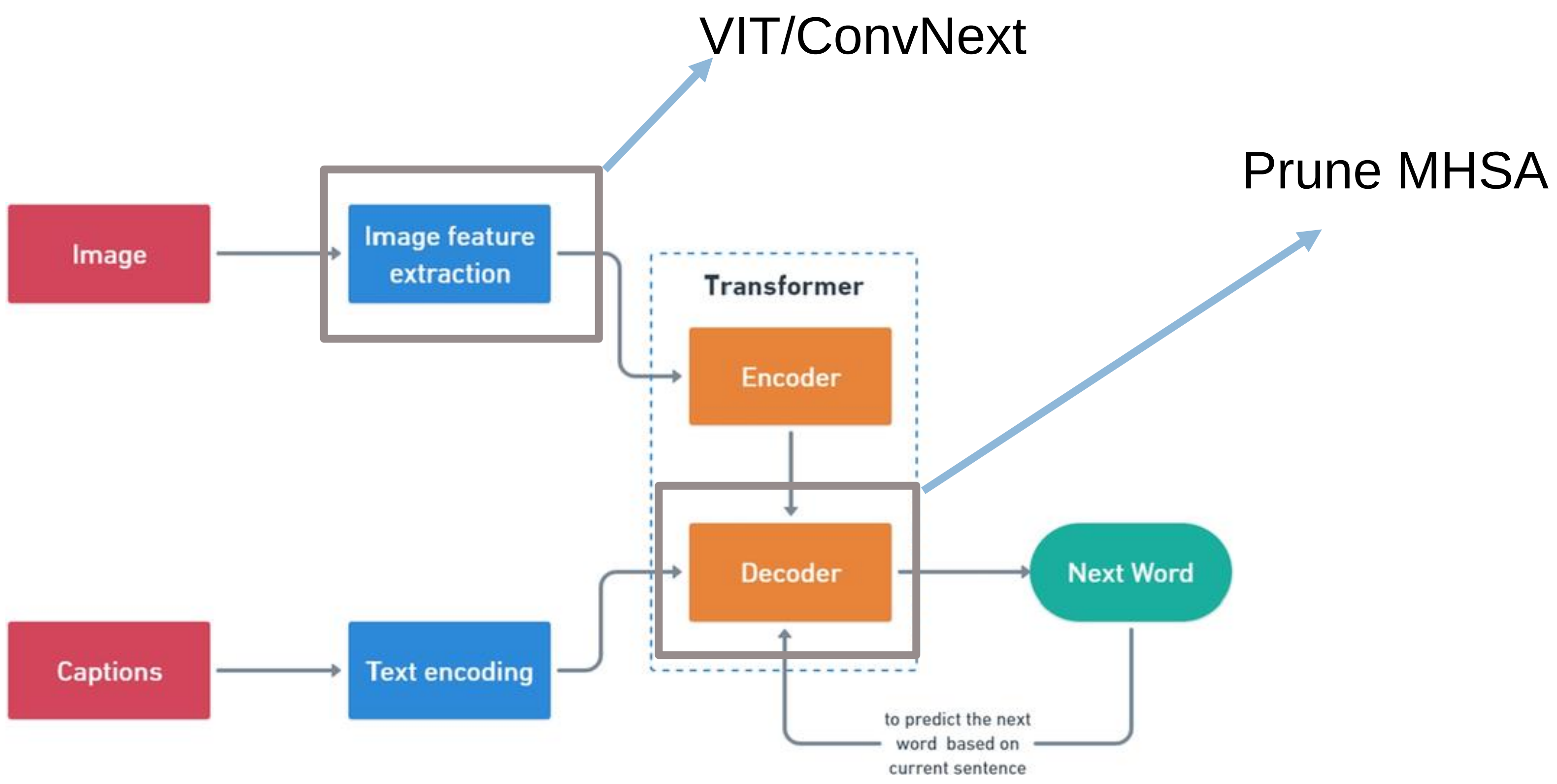
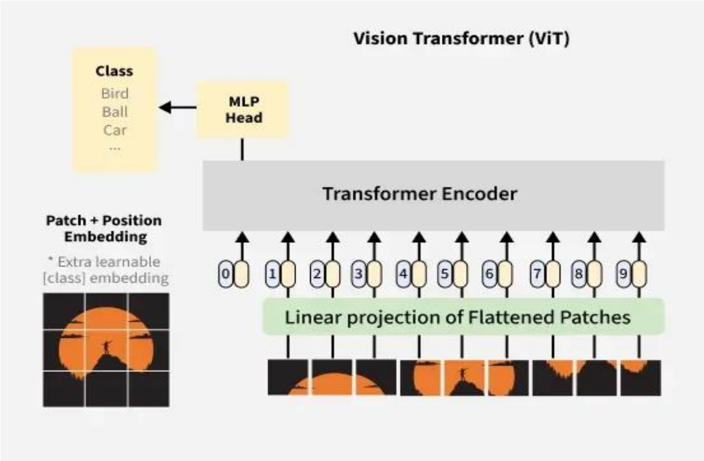
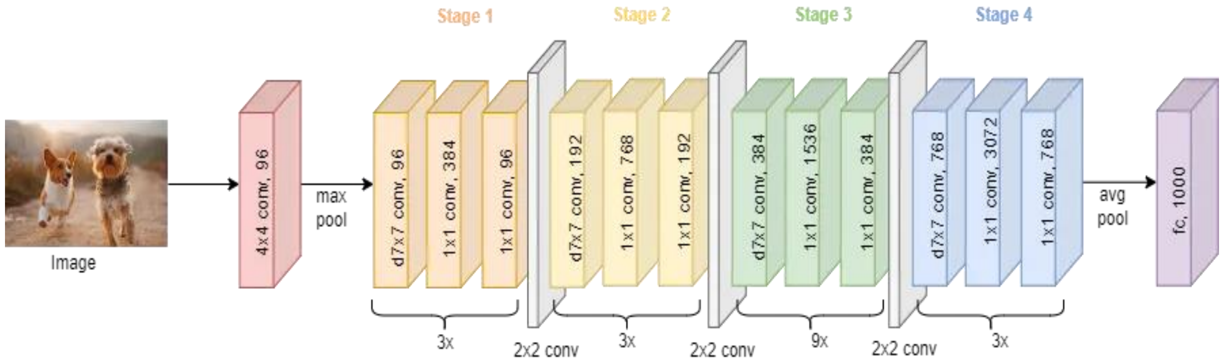
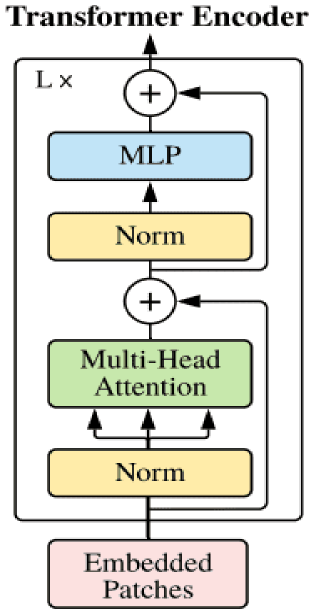
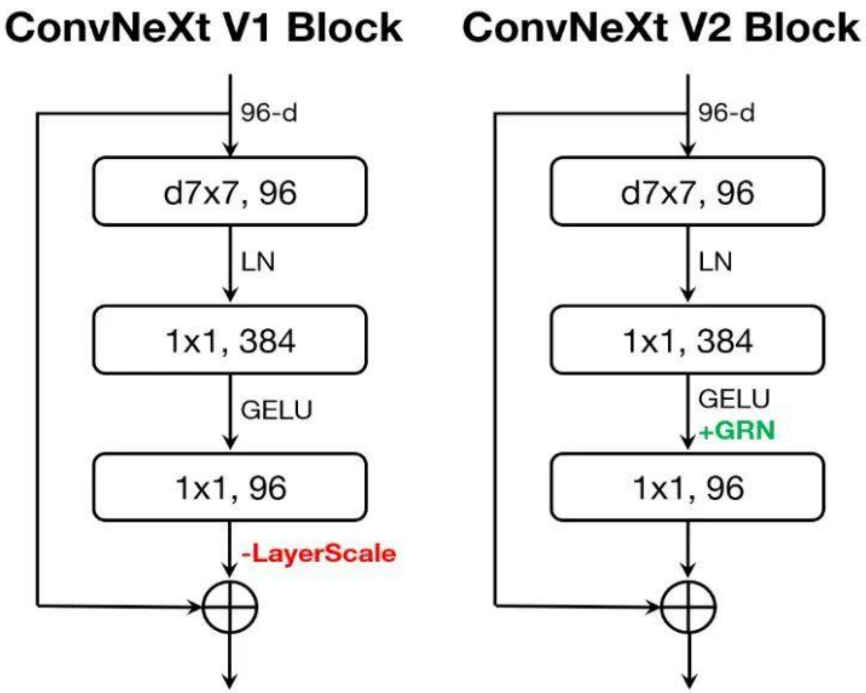


Image feature extraction (VIT and Convnext)

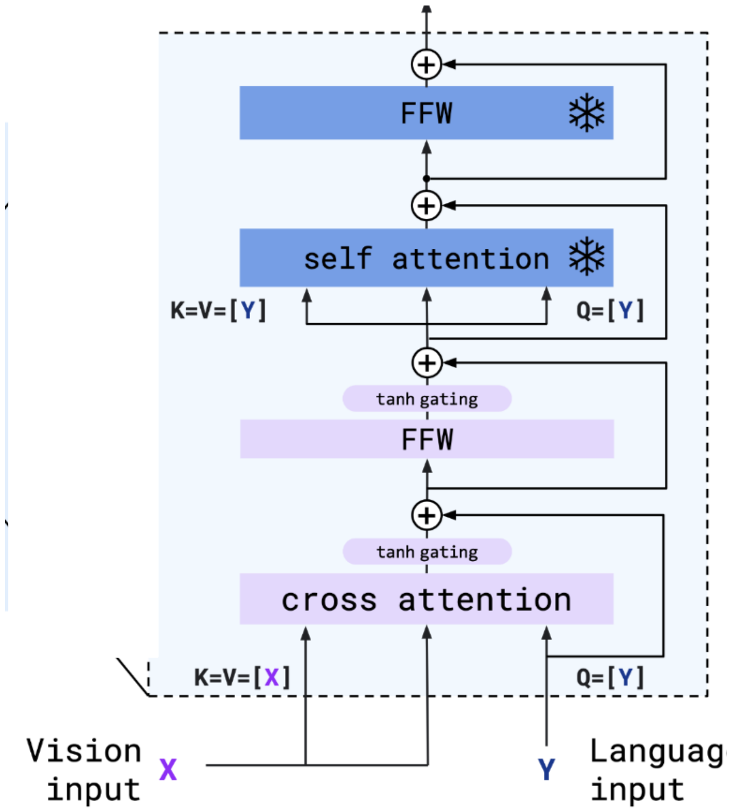






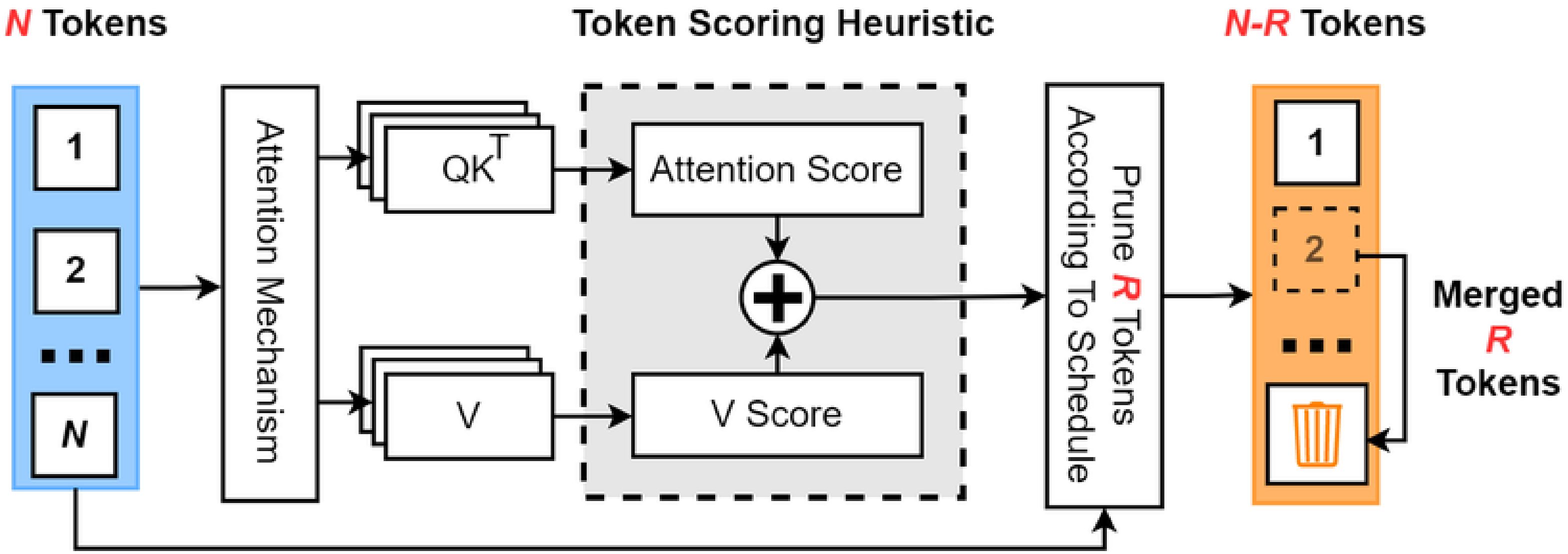


Decoder



MHSA with Cross-Attention is Key part of image captioning because find the correlation of image-text

Token Prune illustration



BEFORE PRUNE

AFTER PRUNE

HOW we BUILD image captioning

- Vision Transformer (ViT) or ConNext as Encoder
- Projection Layer (to ensure image and text have same dimention)
- Tokenization and Positional Embedding
  - Tokenizer (Converts ground truth captions into token IDs using a vocabulary)
  - PosEmbedding (Embeds token IDs into vectors ([batch, seq_len, d_model]), Adds positional encodings to preserve word order.)
- Masking Mechanisms
  - Padding Mask: Prevents attending to <PAD> tokens.
  - Subsequent Mask: Prevents a word from attending to future words during training (causal masking).
- Transformer Decoder
  - Cross-Attention with token pruning: Attend to visual features from visual encoder.
  - Feed-Forward Network (FFN): Non-linear transformation.
- Output Layer (Caption Generation)

Training Strategy and hyperparameter

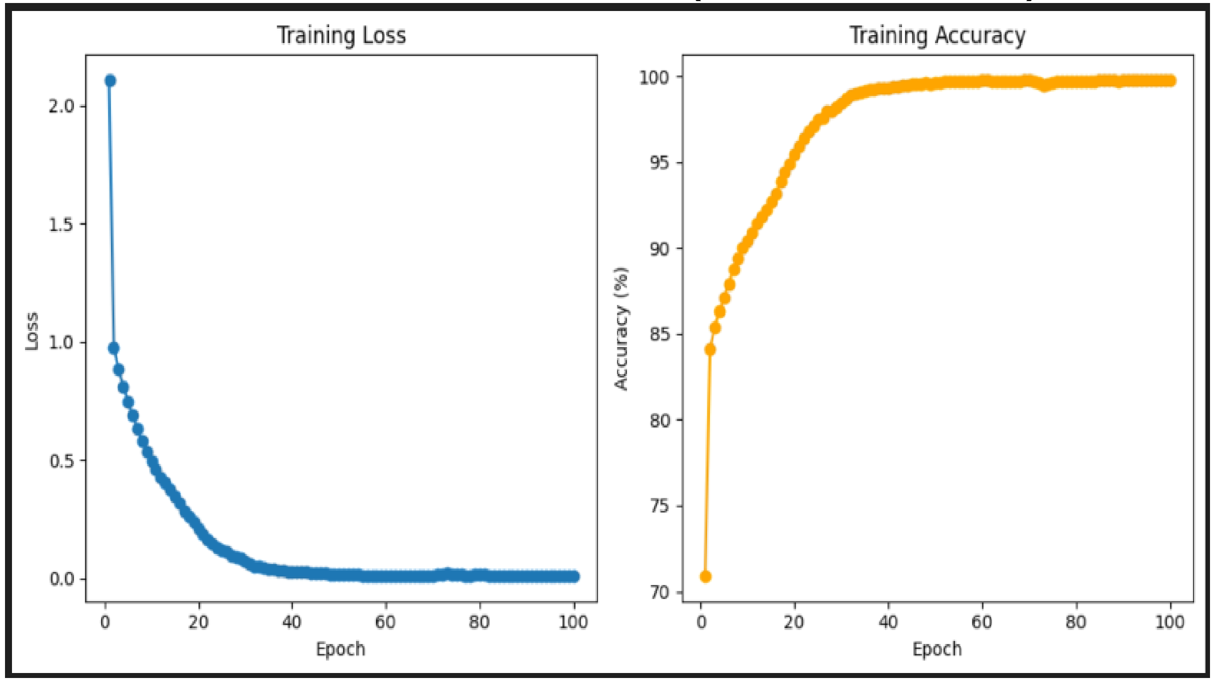
- batch_size = 128
- num_epochs = 100
- patch_dim = 768
- vocab_size = 2033
- d_model = 512
- n_layers = 2
- nhead = 4
- ff_dim = 2048
- dropout_ratio = 0.1
- learning_rate = 0.001

- Dataset = coco image captioning (14GB)
- Prune ratio = 30%

(train in single RTX4090, before use prune the batch size maximum=48)

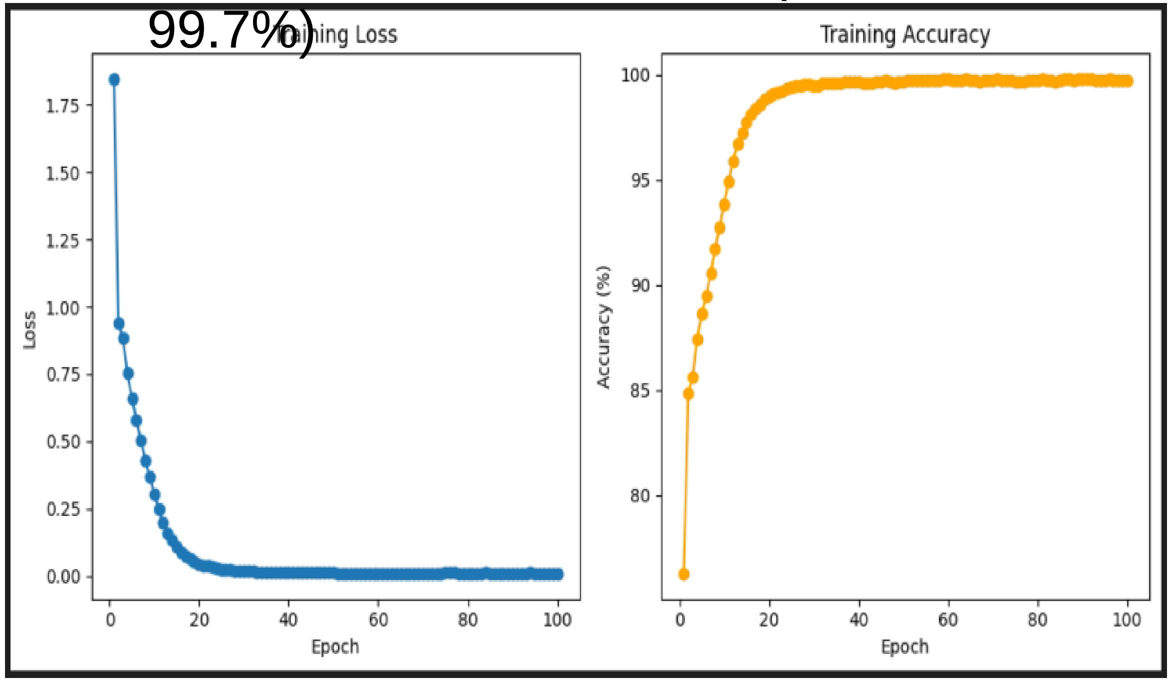
Training Result

VIT BACKBONE (ACC = 99.8%)




```
Epoch 97/100 | 100%|          | 8/8 [00:15<00:00,  1.96s/it, acc=99.78%, loss=0.0001]
Epoch 98/100 | 100%|          | 8/8 [00:15<00:00,  1.91s/it, acc=99.80%, loss=0.0001]
Epoch 99/100 | 100%|          | 8/8 [00:15<00:00,  1.95s/it, acc=99.78%, loss=0.0001]
Epoch 100/100 | 100%|          | 8/8 [00:15<00:00,  1.91s/it, acc=99.80%, loss=0.0001]
```

CONVNEXT BACKBONE (ACC = 99.7%)




```
Epoch 97/100 | 100%|          | 16/16 [00:16<00:00,  1.01s/it, acc=99.75%, loss=0.0002]
Epoch 98/100 | 100%|          | 16/16 [00:15<00:00,  1.02it/s, acc=99.72%, loss=0.0002]
Epoch 99/100 | 100%|          | 16/16 [00:16<00:00,  1.01s/it, acc=99.70%, loss=0.0002]
Epoch 100/100 | 100%|          | 16/16 [00:16<00:00,  1.02s/it, acc=99.70%, loss=0.0002]
```

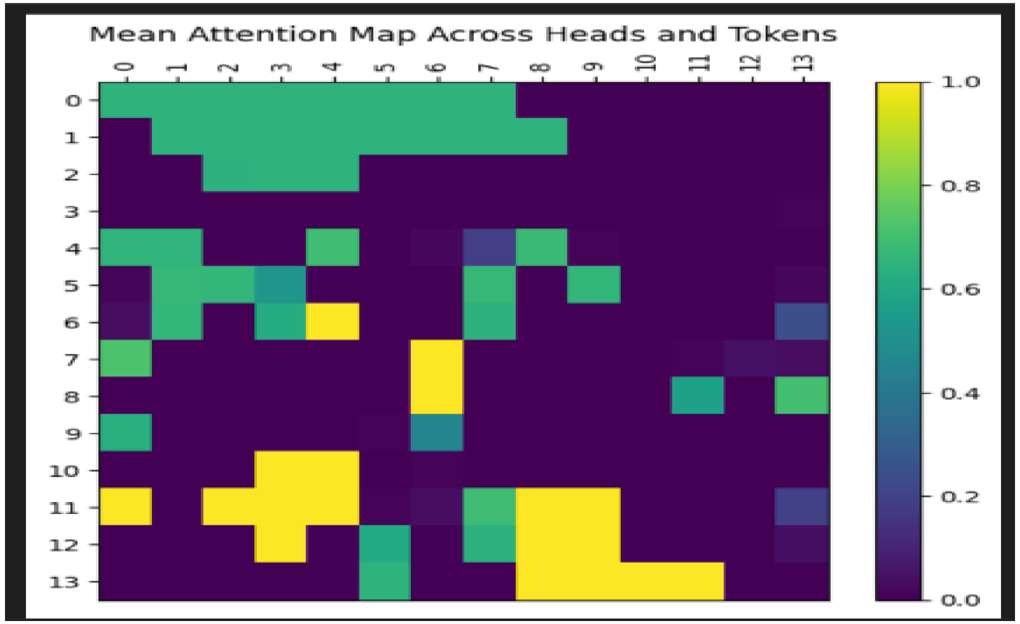
Real world testing

```
A group of people walking along a snow covered slope,
tensor([  1,  12,  89,   8,  10,  93, 301,  12, 350, 624, 983,  92,   2,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0])

<matplotlib.image.AxesImage at 0x748543dfc190>
```

Real world testing

MEAN ATTENTION MAP (SCALING)



Conclusion

- Summary
  - We compared Vision Transformer (ViT) and ConvNeXt architectures for the image captioning task, integrating token pruning to reduce computation. Both models were evaluated based on caption quality, efficiency.
- Key Findings
  - ViT with token pruning preserved semantic richness but was more sensitive to pruning rate.ConvNeXt, a modern CNN, showed greater robustness to token pruning with better speed-performance trade-off.Token pruning significantly improved efficiency with minimal loss in caption accuracy for both models.