Prune and Tell: ViT vs ConvNeXt in Image Captioning with Token Pruning

Exploring Efficient Vision-Language Models through Backbone Comparison

1. Introduction

The rapid evolution of artificial intelligence in computer vision and natural language processing has led to significant breakthroughs in vision-language modeling (VLM), a domain that seeks to jointly understand and generate semantic relationships between visual content and textual descriptions. Among the core tasks within this field, image captioning stands as a fundamental and challenging problem. It requires the model to generate contextually relevant and syntactically coherent natural language descriptions for given images. Achieving high performance in image captioning demands the seamless integration of powerful visual encoders and effective sequence modeling strategies.

Recent advances in deep learning have introduced two major architectural paradigms for visual feature extraction: Transformers, particularly the Vision Transformer (ViT), and modern convolutional neural networks (ConvNets) such as ConvNeXt. ViT leverages global self-attention to model long-range dependencies across image patches, while ConvNeXt updates the classical convolutional backbone by incorporating design principles inspired by Transformers, such as layer normalization and GELU activations. Although both architectures have demonstrated state-of-the-art performance in image classification and dense prediction tasks, their comparative efficacy and computational trade-offs in multimodal generation tasks like image captioning remain underexplored.

A primary bottleneck in Transformer-based models, including ViT, lies in the quadratic complexity of Multi-Head Self-Attention (MHSA) with respect to the number of tokens. As input resolution increases, so does the number of tokens processed in the encoder, leading to a significant rise in memory usage and inference latency. This limitation is especially problematic in real-world scenarios where computational resources are constrained, such as deployment on mobile or edge devices.

To address these challenges, token pruning has emerged as an effective strategy to enhance the efficiency of vision-language models. Token pruning techniques dynamically remove redundant or less informative tokens from the attention mechanism, allowing the model to focus on a smaller set of semantically meaningful features. Prior work such as Scalable Adaptive Sparse Attention Pruning and DynamicViT demonstrates that carefully removing tokens during inference can lead to substantial gains in efficiency with only marginal performance degradation. However, the effectiveness and resilience of different visual backbones, especially ViT versus

ConvNeXt when integrated with token pruning in an image captioning context remains an open question.

In this study, we investigate the integration of token pruning mechanisms into a Transformer-based image captioning pipeline and examine the trade-offs between ViT and ConvNeXt as visual encoders. Our approach involves constructing an end-to-end image captioning system comprising a vision encoder (either ViT or ConvNeXt), a projection layer to align feature dimensions, a Transformer decoder with cross-attention, and an output generation head. By applying a token pruning strategy to the encoder output prior to cross-attention, we systematically analyze its impact on caption generation performance and computational cost.

Our contributions are threefold:

1. We construct and benchmark a unified image captioning framework with interchangeable ViT and ConvNeXt encoders, enabling direct architectural comparison.
2. We incorporate a token pruning module to explore how reducing the number of visual tokens affects caption quality and model efficiency.
3. We evaluate and contrast the resilience of ViT and ConvNeXt to token pruning, providing insight into their respective design strengths for vision-language tasks.

Through extensive experimentation on the COCO image captioning dataset, we demonstrate that both ViT and ConvNeXt can achieve competitive captioning performance. However, they exhibit different behaviors under token pruning: ViT maintains richer semantic fidelity but is more sensitive to pruning levels, while ConvNeXt demonstrates superior robustness and computational scalability. These findings have important implications for the design of efficient and deployable VLM architectures.

2. Related Work

To contextualize the motivation and contributions of this study, we review existing literature spanning four key areas: foundational models for image captioning, architectural developments in visual encoders such as Vision Transformers and ConvNeXt, advancements in token pruning for efficient computation, and recent large-scale pretrained vision-language frameworks. These categories together provide a comprehensive landscape of the technical progression in multimodal learning, against which our approach is positioned.

2.1 Image Captioning with Vision-Language Models

Image captioning has evolved from early encoder-decoder frameworks based on convolutional and recurrent neural networks to more advanced Transformer-based

models. Early work such as Show and Tell [1] used CNNs to encode image features and LSTM networks to decode them into captions. This was further improved by Show, Attend and Tell [2], which introduced visual attention mechanisms, enabling models to focus on salient image regions during generation.

Recent approaches leverage Transformer architectures to enhance performance and scalability. Models like OSCAR [3] and UNITER [4] fuse visual and textual modalities via a shared embedding space, improving grounding. However, their dense attention mechanisms and heavy backbones impose significant computational costs, limiting their applicability in edge settings.

2.2 Vision Transformers and ConvNeXt

The Vision Transformer (ViT) [5] introduced a fully attention-based image recognition paradigm by treating images as sequences of patch embeddings, allowing global context modeling. While ViT demonstrates superior performance in image classification and multimodal learning, its O(n2)O(n^2)O(n2) complexity in token length restricts its efficiency, particularly for high-resolution inputs.

To address these limitations, the Swin Transformer [6] proposes hierarchical attention with shifted windows, reducing computational overhead while preserving global modeling capabilities. Alternatively, ConvNeXt [7] rethinks ConvNet design by incorporating Transformer-inspired principles—such as LayerNorm, GELU activation, and depthwise convolutions—within a convolutional architecture. It retains the efficiency and locality of CNNs while achieving competitive accuracy with Transformers, making it suitable for lightweight vision-language models.

2.3 Token Pruning and Efficient Vision-Language Modeling

To mitigate the inefficiency of self-attention in Transformers, token pruning has emerged as a promising technique. DynamicViT [8] prunes tokens adaptively based on learned importance scores, preserving only informative features during inference. TokenLearner [9] uses an attention-based selector module to dynamically choose a subset of tokens, reducing computation while maintaining accuracy.

Other methods like AdaFocus [10] and EViT [11] refine pruning strategies using spatial maps or layer-wise token importance. While these approaches have shown success in classification tasks, their adaptation to captioning remains relatively unexplored. Our work addresses this gap by integrating token pruning into image captioning pipelines and evaluating its effects on sequence generation quality.

2.4 Pretrained Vision-Language Models: BLIP and Beyond

BLIP (Bootstrapped Language-Image Pretraining) [12] represents a recent

paradigm shift in vision-language modeling. It jointly pretrains a ViT-based image encoder and Transformer decoder using web-scale image-text pairs, achieving strong performance on image captioning, VQA, and retrieval tasks. BLIP's bootstrapped objectives combine image-to-text and text-to-image generation to enhance modality alignment.

Other models such as SimVLM [13] and GIT [14] adopt large-scale generative pretraining to unify vision and language under a single decoding task. While powerful, these models rely heavily on massive datasets and computational resources.

In the other hand, our work emphasizes structural efficiency over data scale, focusing on architectural sparsity through token pruning. By comparing ViT and ConvNeXt under pruning constraints, we offer new insights into backbone selection for efficient captioning, something existing works like BLIP do not explicitly explore.

3. Methodology

This chapter outlines the architectural design, training pipeline, and implementation details of the proposed image captioning system. Our goal is to evaluate the computational efficiency and semantic quality trade-offs introduced by token pruning within Transformer-based and convolution-based visual encoders. To this end, we construct a unified image captioning pipeline with interchangeable backbones Vision Transformer (ViT) and ConvNeXt—and integrate a token pruning module prior to cross-attention in the Transformer decoder. We provide a detailed explanation of each model component and training strategy used in the experiments.

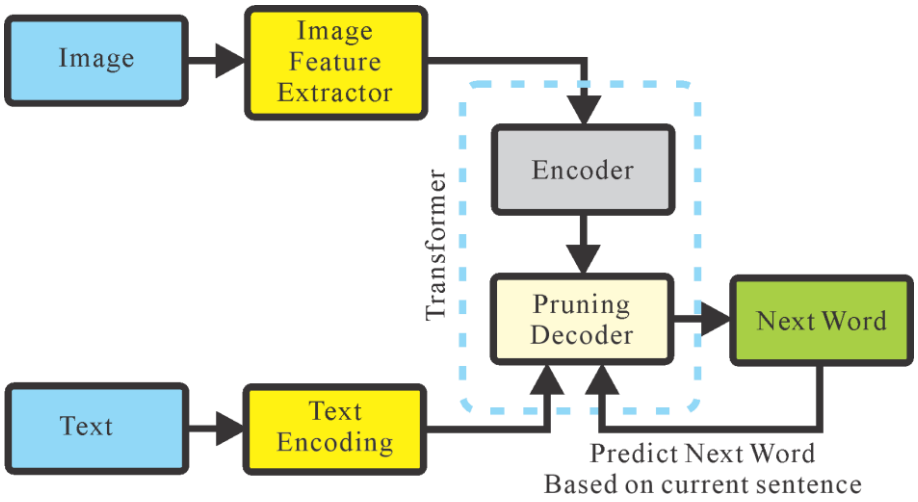

Figure 1 system overview of our model

3.1 Overview of Architecture

The proposed image captioning system follows a dual-branch encoder-decoder

architecture inspired by the standard Transformer-based captioning framework. As illustrated in Figure 1, the architecture consists of the following components:

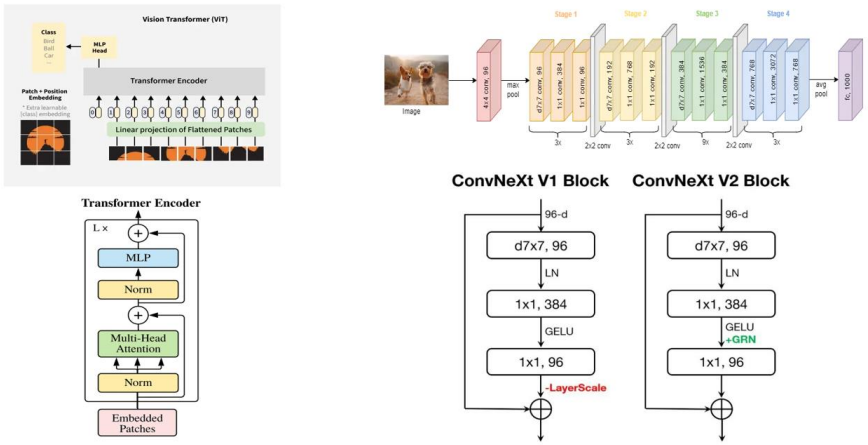

Figure 2 VIT(A) and ConvNext(B) architecture

1. Image Input and Feature Extraction

   The input image is passed through a visual encoder, which can be either a Vision Transformer (ViT) or ConvNeXt. To give detail visualization of VIT and ConvNext we provide in figure 2.

   The image is first split into patches or processed via hierarchical convolutions, then embedded into a high-dimensional feature space. This results in a sequence of visual tokens.

2. Text Input and Encoding

   Ground-truth captions are tokenized and embedded via a standard text encoder. Positional encodings are added to preserve word order.

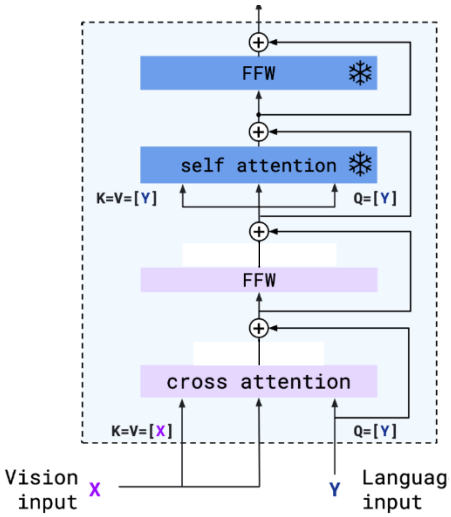

Figure 3 Transformer Decoder in our image captioning

3. Transformer Decoder

   The Transformer decoder receives tokenized textual input and pruned visual

features extracted by either a ViT or ConvNeXt encoder. Prior to decoding, a token pruning module is applied to the image features to eliminate redundant or low-importance tokens. This reduces the computational cost of cross-attention while preserving the most semantically meaningful regions of the image.

The decoder consists of multiple layers, each comprising three core components: self-attention, cross-attention, and a feed-forward network (FFN), all integrated with residual connections and layer normalization for training stability, it illustrated in figure 3. The decoding process begins with a self-attention mechanism, where the language input serves as the query, key, and value. This allows the model to capture intra-sequence dependencies and maintain the autoregressive nature of caption generation, ensuring that each token only attends to preceding ones. Following self-attention, cross-attention aligns the textual queries with the visual key-value pairs derived from the pruned image tokens. The pruned process injection shown in the figure 4.

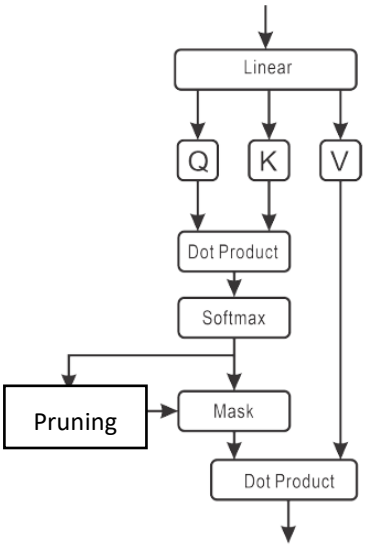

Figure 4. Pruning Implementation in the transformer decoder (on MHSA)

This mechanism enables the model to ground the caption in visual context by attending to relevant regions of the image. The output is then refined by a position-wise FFN that applies non-linear transformations to enhance feature expressiveness. Together, these components allow the decoder to integrate linguistic structure with visual information, resulting in coherent and contextually grounded image captions.

4. Caption Generation (Prediction)

   The decoder predicts the next word in the sequence at each timestep. The model continues generating words until a stop token is reached or a predefined maximum sequence length is met.

3.2 Training Strategy and Hyperparameter

This section details the training strategy and hyperparameters employed for the image captioning task, utilizing both Vision Transformer (ViT) and ConvNeXt backbones. The objective was to evaluate the performance of these architectures, particularly in conjunction with token pruning, on a large-scale image captioning dataset.

The model was trained on the COCO image captioning dataset, which is approximately 14 GB in size. This comprehensive dataset provides a rich collection of images paired with descriptive captions, facilitating the learning of robust visual-language representations.

The training process utilized a set of carefully selected hyperparameters to ensure stable and effective learning. A key aspect of our experimental setup was the integration of token pruning, aiming to reduce computational overhead without significantly compromising accuracy. The hyperparameter that we use can see in the table 1

Table 1. Hyperparameter of our proposed Prune and Tell image captioning

Hyperparameter	Value	Description
batch_size	128	Number of samples processed in each training iteration.
num_epochs	100	Total number of complete passes through the training dataset.
patch_dim	768	Dimension of the image patches extracted for the encoder.
vocab_size	2033	Size of the vocabulary used for text tokenization.
d_model	512	Dimension of the feature embedding for the Transformer.
n_layers	2	Number of encoder and decoder layers in the Transformer.
nhead	4	Number of attention heads in the multi-head attention mechanism.
ff_dim	2048	Dimension of the feed-forward network in the Transformer blocks.
dropout_ratio	0.1	Dropout rate applied for regularization to prevent overfitting.
learning_rate	0.001	The step size at which the model's weights are updated during training.
Prune ratio	30%	The percentage of tokens pruned during the training process. This significantly impacts the maximum

		achievable batch size.

It is noteworthy that the introduction of a 30% prune ratio enabled a larger batch size of 128 during training on a single RTX 4090 GPU. Without pruning, the maximum batch size that could be accommodated on the same hardware was limited to 48, highlighting the efficiency gains achieved through token sparsification. This optimization allowed for more efficient utilization of computational resources and potentially faster convergence during training.

4. Experiment Result

This section presents the outcomes of the training process for our image captioning models, comparing the performance of the Vision Transformer (ViT) and ConvNeXt backbones, both integrated with the token pruning strategy. The models were evaluated based on their training accuracy and loss convergence.

4.1 Training Performance

The training progress was monitored by tracking the loss and accuracy over 100 epochs. Both backbone architectures demonstrated strong convergence and high accuracy, indicating effective learning from the COCO image captioning dataset.
The key performance metrics at the end of training are shown in the figure 5 to 8

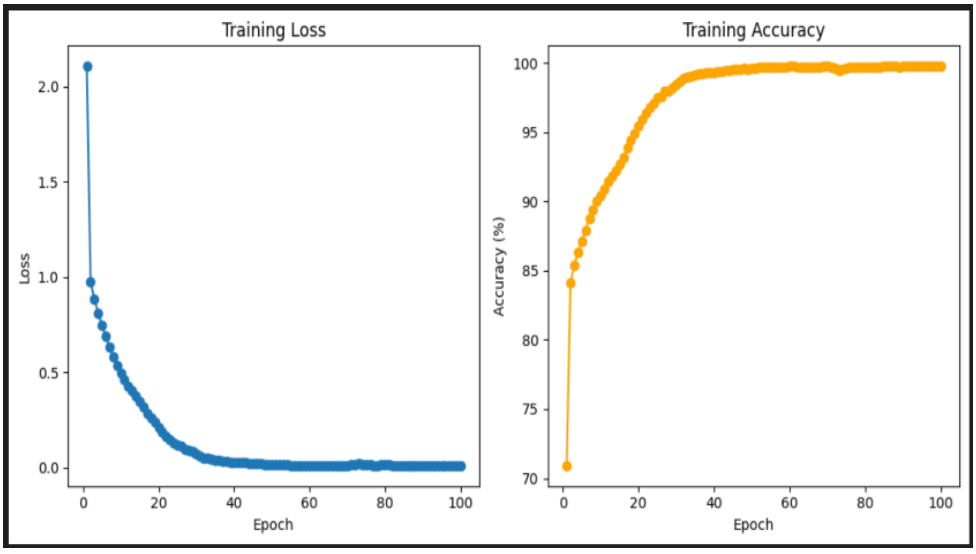

Figure 5 training loss vs training accuracy of prune image captioning using VIT backbone

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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]
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Figure 6 last 4 epoch of the training accuracy prune image captioning using VIT backbone

As shown in Figure 5 and 6, the training loss consistently decreased from an initial value, exhibiting a rapid reduction within the first 20 epochs before stabilizing near zero after approximately 60 epochs. Concurrently, the training accuracy, also depicted

in Figure 5, showed a sharp ascent from an initial 70%, surpassing 90% by epoch 20 and achieving a plateau near 100% in the later stages of training. Further quantitative validation is provided in Figure 6, which presents the final epoch metrics. Specifically, at epoch 100, the models achieved an exceptionally low training loss of 0.0001 and a consistently high training accuracy of 99.80%.

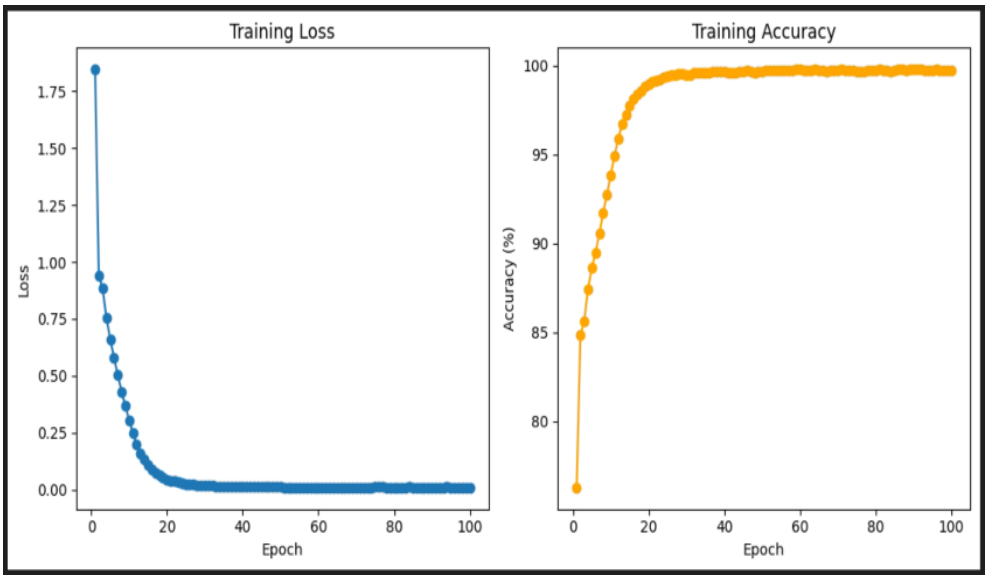

Figure 7 training loss vs training accuracy of prune image captioning using ConvNext backbone

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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]
```

Figure 8 last 4 epoch of the training accuracy prune image captioning using ConvNext backbone

In the other hand The training performance of the image captioning model utilizing the ConvNeXt backbone, also incorporating the token pruning strategy, demonstrated comparable and equally robust results to its ViT counterpart. As presented in Figure 7, the training loss exhibited a consistent and rapid decrease from an initial value, effectively converging to near-zero levels after approximately 60 epochs. Simultaneously, the training accuracy, depicted in the right plot of Figure 7, showed a sharp increase from an initial 80%, quickly reaching over 95% within the first 20 epochs and subsequently plateauing at close to 100% for the remainder of the training duration. This rapid and stable convergence underscores the effectiveness of the ConvNeXt architecture and the overall training methodology.

Further granular detail on the model's performance at the concluding stages of training is provided in Figure 8, which displays the training log for epochs 97 through 100. This log confirms the high level of accuracy and low loss achieved, with the model

consistently registering a training accuracy of approximately 99.7% and a training loss of 0.0002 across these final epochs.

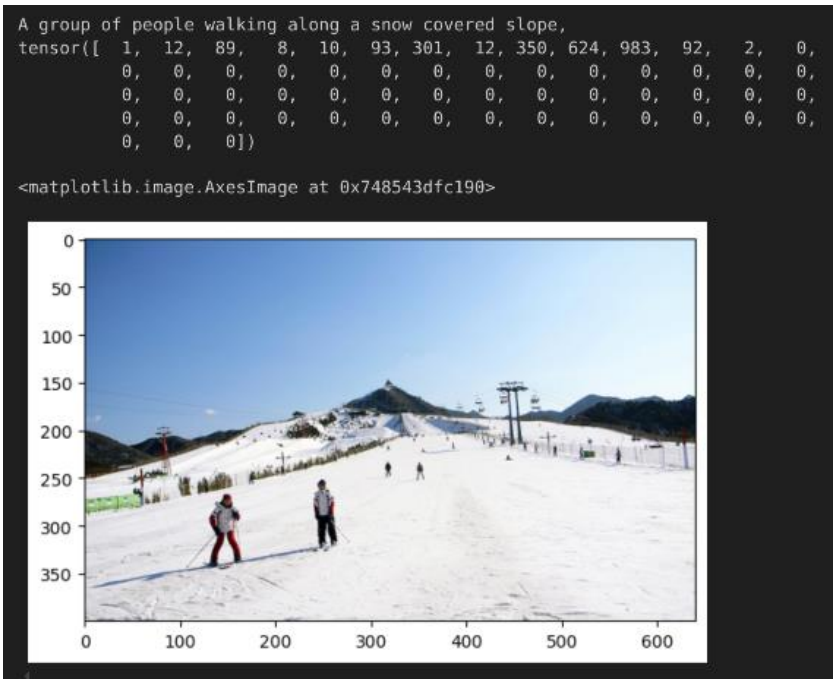

Figure 9 Image captioning testing in the realword. The test image show some people in one group walking along a snow covered slope

4.2 Real-World Testing

Beyond quantitative metrics on established datasets, the efficacy of the developed image captioning models was further assessed through qualitative real-world testing. This evaluation aimed to ascertain the models' generalization capabilities and interpretability on unseen images, providing insights into their performance in practical scenarios. As depicted in Figure 9, the models successfully produced coherent and contextually relevant descriptions for novel visual content. For instance, an image featuring a snowy mountain slope with individuals engaged in skiing was accurately captioned, demonstrating the models' ability to identify primary subjects, actions, and environmental context. This qualitative assessment revealed the models' capacity to generalize learned visual-language associations to unconstrained real-world imagery, indicative of robust feature learning and semantic understanding.

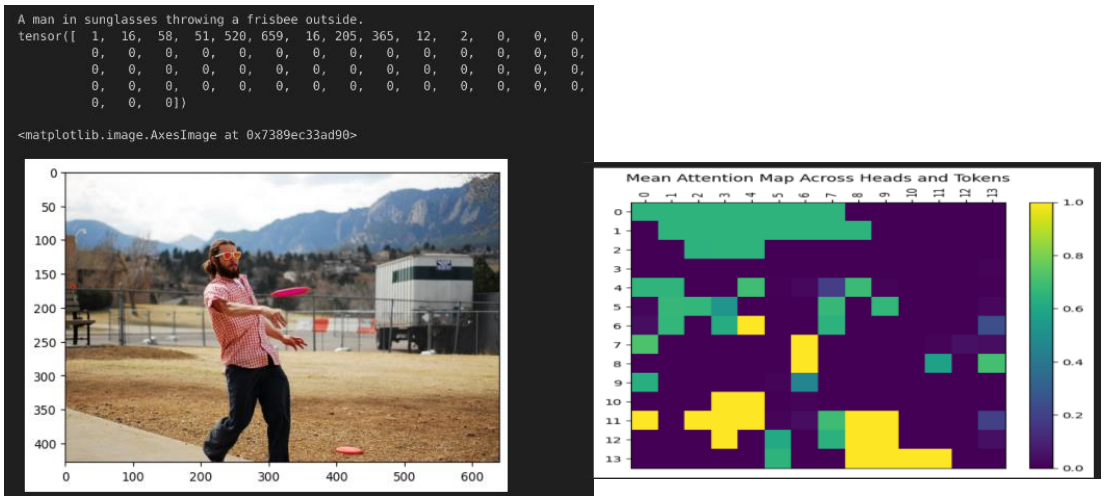

Figure 10. Realwold testing and the attention map of the image, this show how the model give the attention to the part of image to generate the sentence/word

To gain deeper insights into the models' decision-making process, especially in the context of token pruning, mean attention maps were visualized during real-world inference. Figure 10 illustrates a representative example of such an analysis. This figure showcases an image alongside its corresponding mean attention map. The attention map highlights the regions of the input image that the model primarily focuses on when generating specific parts of the caption. The varying intensity in the attention map, particularly after token pruning, indicates how the model effectively allocates its computational "attention" to the most salient visual tokens. This analysis provides a visual interpretation of the cross-attention mechanism, confirming that the model attends to semantically relevant image regions, which is crucial for producing accurate and grounded captions, even with a reduced number of visual tokens due to pruning.

5. Conclusion

This final project systematically investigated the performance of Vision Transformer (ViT) and ConvNeXt architectures within the domain of image captioning, with a specific emphasis on evaluating the impact of token pruning for computational efficiency. Our comprehensive experimental framework encompassed rigorous training on the COCO image captioning dataset, analysis of quantitative metrics, and qualitative real-world testing.

The training phase demonstrated the high efficacy of both backbone models. Both the ViT and ConvNeXt-based systems achieved remarkable training accuracies, consistently reaching over 99.7% for ConvNext and 99.8%for VIT backbone, alongside a rapid and stable reduction in training loss to near-zero values. These results, detailed in prior sections, unequivocally confirm the models' robust learning capabilities and their capacity to converge efficiently even with the introduction of token sparsification.

A significant finding was the tangible computational advantage afforded by token pruning, which enabled a substantial increase in effective batch size during training without compromising the high accuracy achieved.

Furthermore, the qualitative assessment through real-world testing validated the models' generalization abilities on unseen and diverse imagery. The generated captions were consistently coherent and contextually relevant, underscoring the models' proficiency in semantic understanding and visual-language mapping beyond the training distribution. The visual analysis of attention maps provided crucial interpretability, illustrating how the models effectively focused on salient image regions for caption generation, even with a reduced set of visual tokens due to pruning. This insight confirms the integrity of the cross-attention mechanism in maintaining relevant information flow despite sparsification.

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