

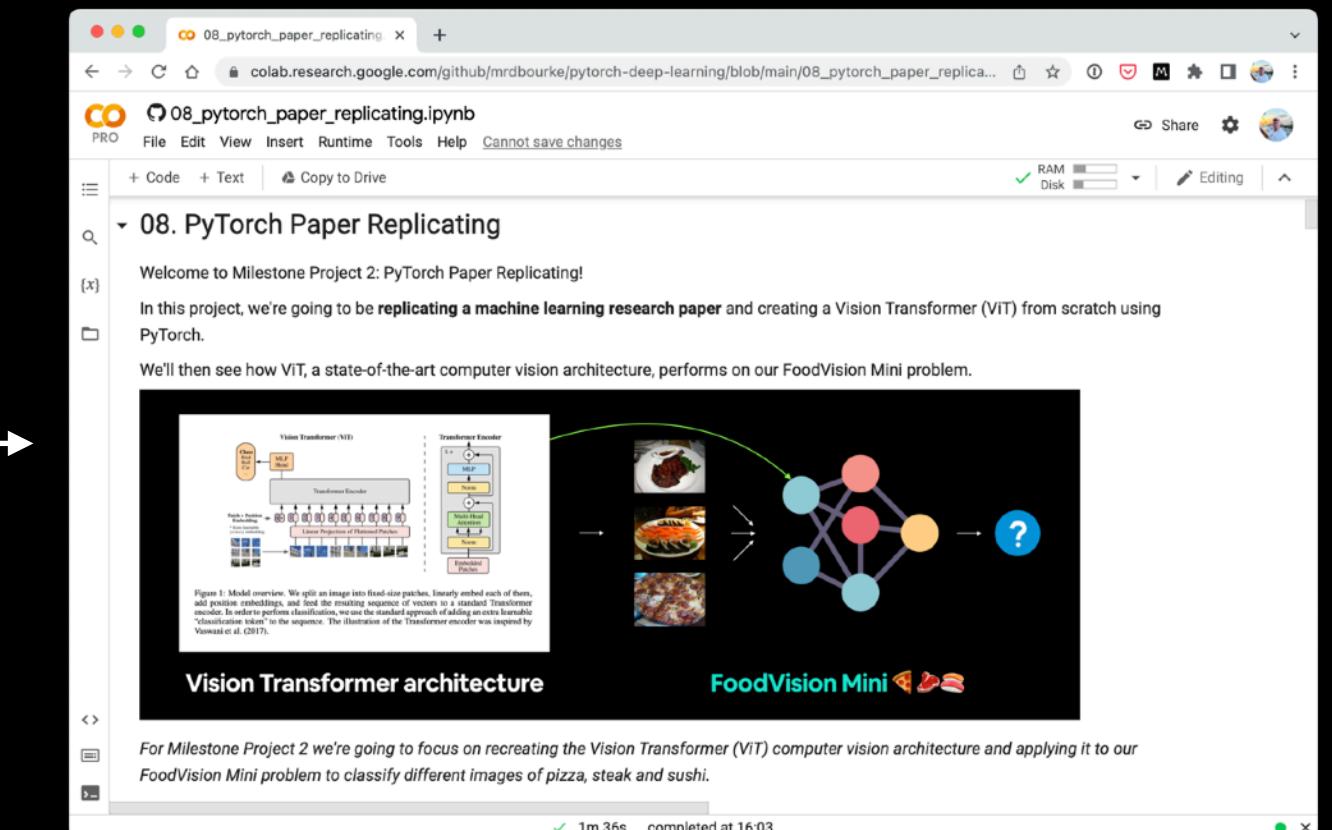
Milestone Project 2

Paper Replicating with



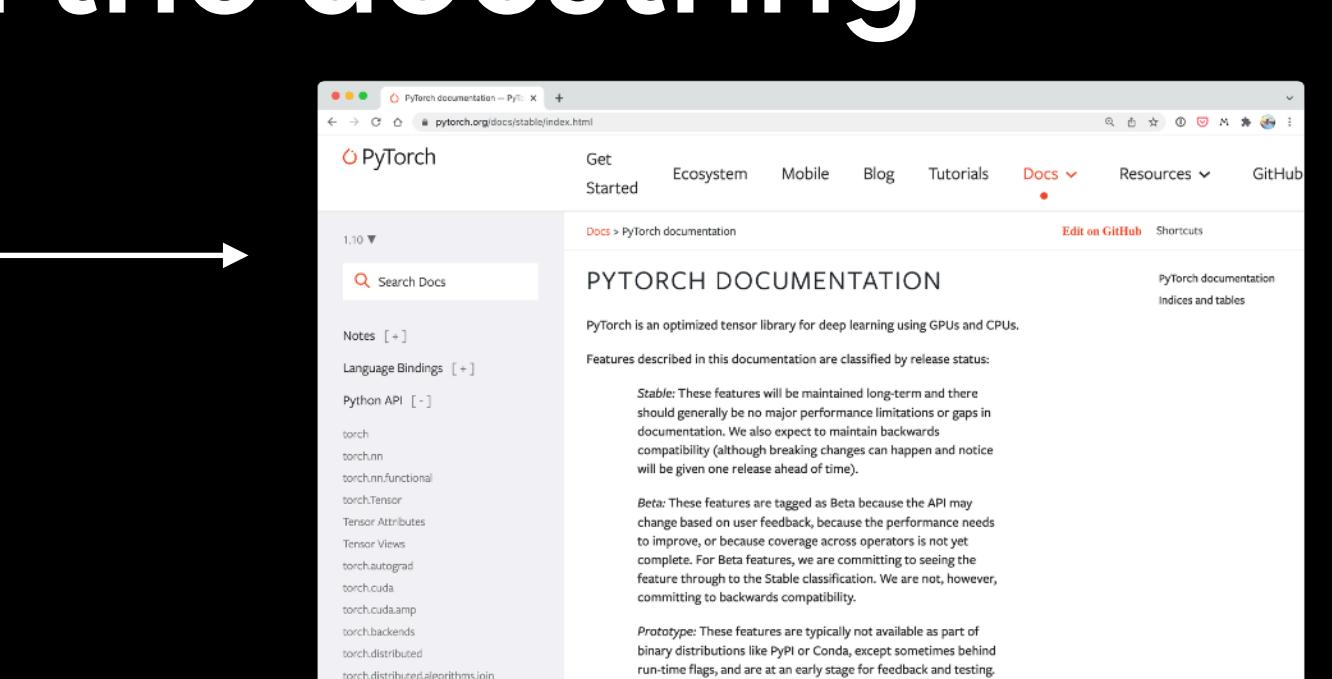
Where can you get help?

- Follow along with the code



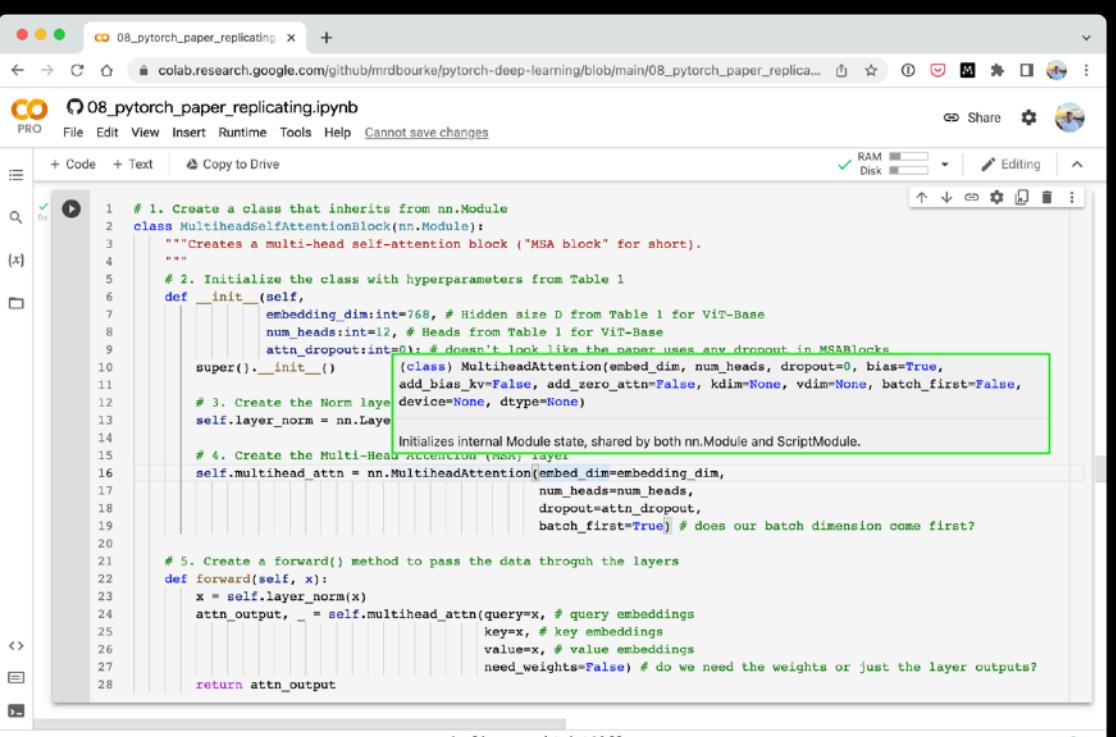
"If in doubt, run the code"

- Try it for yourself



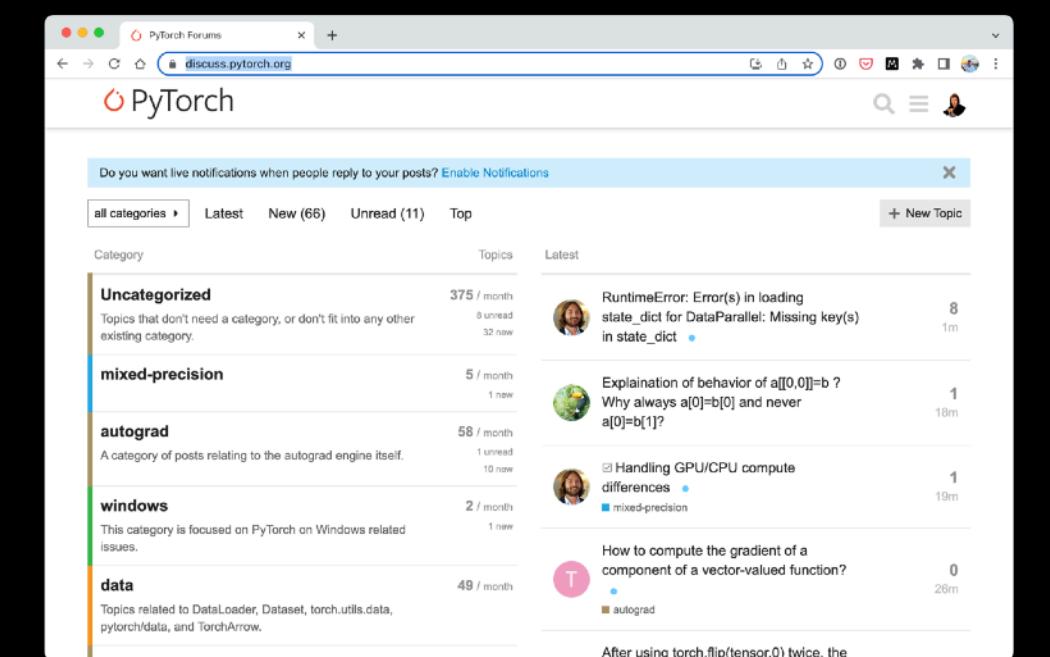
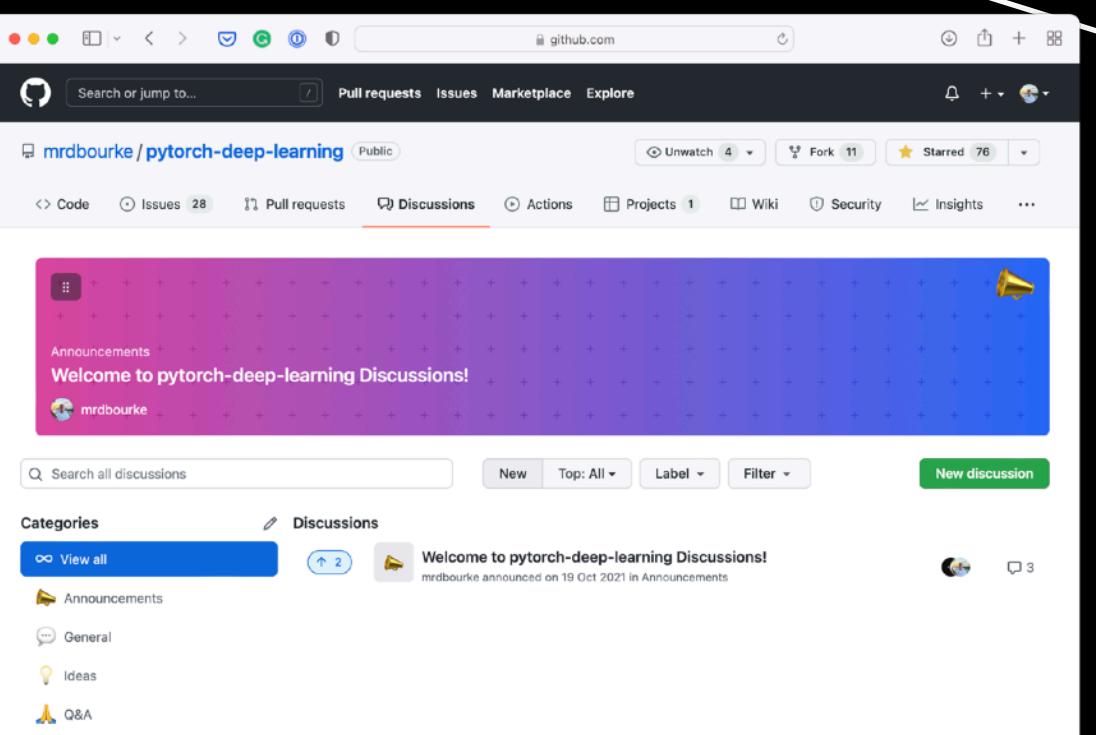
- Press SHIFT + CMD + SPACE to read the docstring

- Search for it



- Try again

- Ask

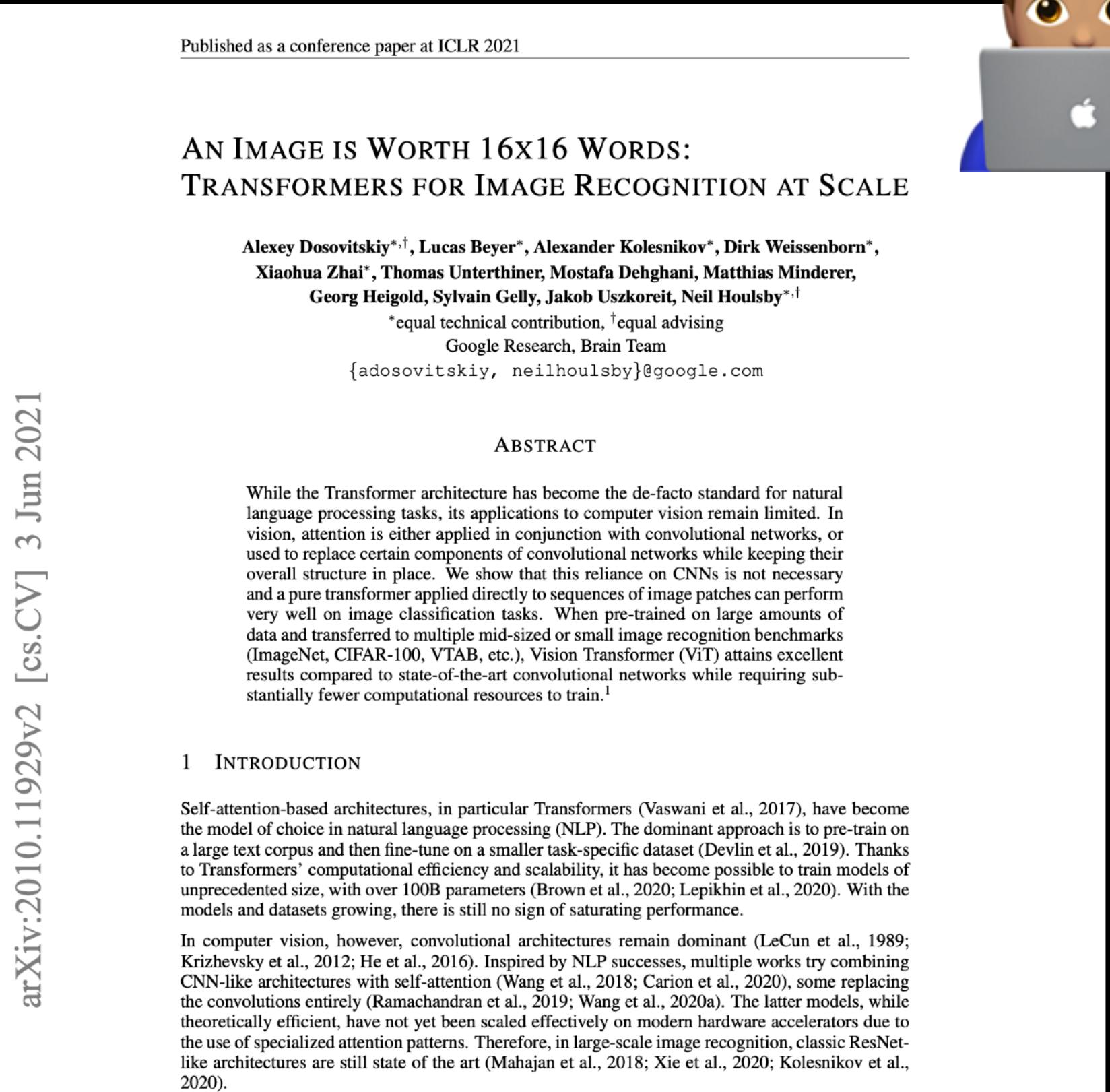


<https://www.github.com/mrdbourke/pytorch-deep-learning/discussions>

“What is machine learning
research paper replicating?”

Turning research into usable code.

What is paper replicating?



arXiv:2010.11929v2 [cs.CV] 3 Jun 2021

Source: <https://arxiv.org/pdf/2010.11929.pdf> (ViT paper)

Machine learning paper



Cooking recipe

What is paper replicating?

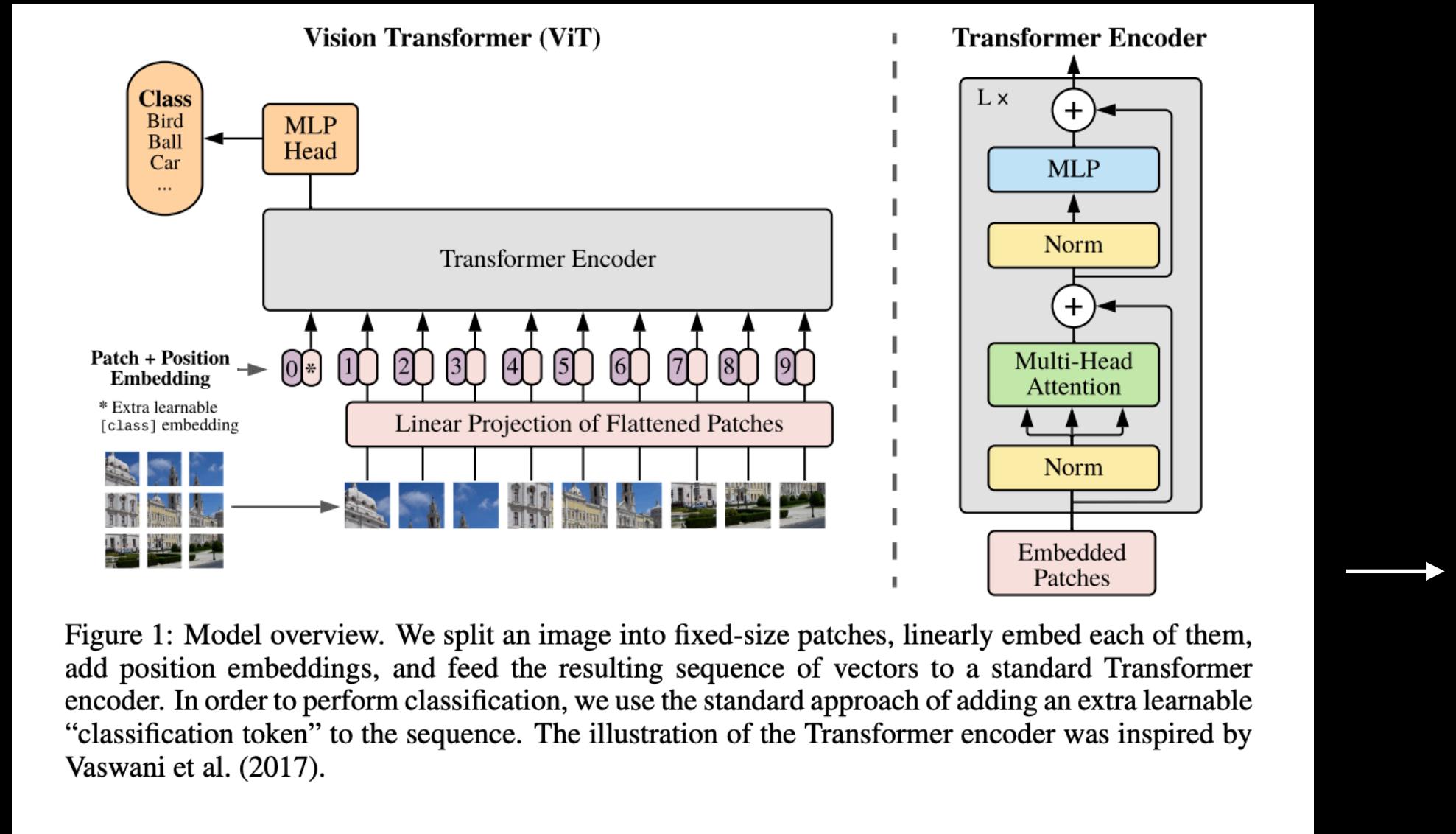


Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable “classification token” to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).

Transformer Encoder

```

import torch as nn

class ViT(nn.Module):
    """Creates a Vision Transformer architecture with ViT-Base hyperparameters by default."""
    def __init__(self,
                 img_size:int=224, # Training resolution from Table 3 in ViT paper
                 in_channels:int=3, # Number of channels in input image
                 patch_size:int=16, # Patch size
                 num_transformer_layers:int=12, # Layers from Table 1 for ViT-Base
                 embedding_dim:int=768, # Hidden size D from Table 1 for ViT-Base
                 mlp_size:int=3072, # MLP size from Table 1 for ViT-Base
                 num_heads:int=12, # Heads from Table 1 for ViT-Base
                 num_classes:int=1000): # Default for ImageNet but can customize this
        super().__init__()

        self.patch_embedding = PatchEmbedding(in_channels=in_channels,
                                              patch_size=patch_size,
                                              embedding_dim=embedding_dim)

        self.transformer_encoder = nn.Sequential(*[TransformerEncoderBlock(embedding_dim=embedding_dim,
                                                                         num_heads=num_heads,
                                                                         mlp_size=mlp_size) for _ in range(num_transformer_layers)])

        self.classifier = nn.Sequential(
            nn.Linear(in_features=embedding_dim, out_features=num_classes)
        )

    def forward(self, x):
        x = self.patch_embedding(x)
        x = self.transformer_encoder(x)
        return self.classifier(x[:, 0])

# Create ViT
vit = ViT()

```

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{\text{pos}}, \quad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{\text{pos}} \in \mathbb{R}^{(N+1) \times D} \quad (1)$$

$$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \quad \ell = 1 \dots L \quad (2)$$

$$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad \ell = 1 \dots L \quad (3)$$

$$\mathbf{y} = \text{LN}(\mathbf{z}_L^0) \quad (4)$$

The Transformer encoder (Vaswani et al., 2017) consists of alternating layers of multiheaded self-attention (MSA, see Appendix A) and MLP blocks (Eq. 2, 3). Layernorm (LN) is applied before every block, and residual connections after every block (Wang et al., 2019; Baevski & Auli, 2019).

Source: [ViT paper](#)

Images + math + text

Usable code

Terminology

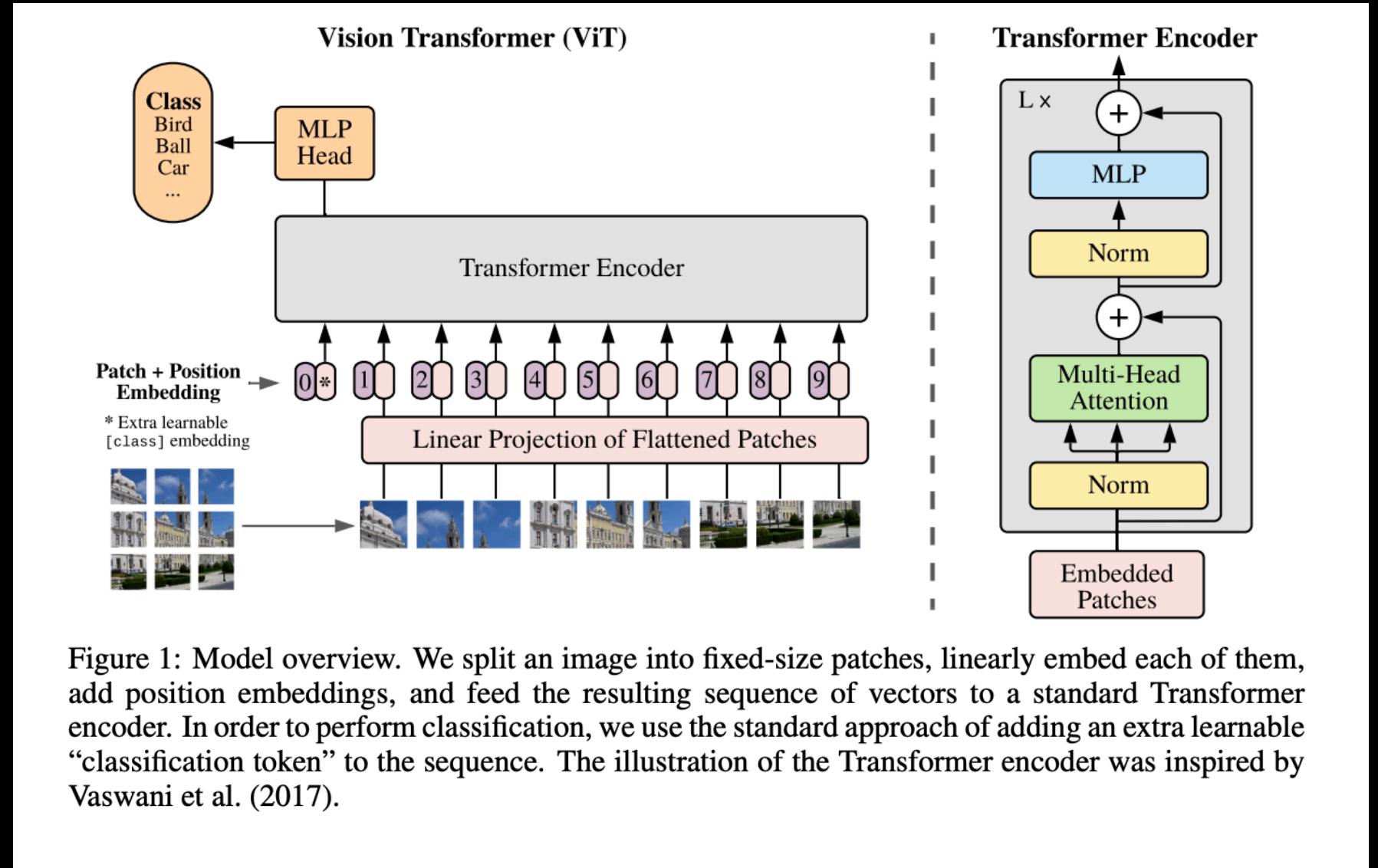


Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable “classification token” to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).



$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{pos}, \quad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{pos} \in \mathbb{R}^{(N+1) \times D} \quad (1)$$

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Source: [ViT paper](#)

Vision Transformer (**ViT**) architecture

ViT paper

Source: <https://arxiv.org/pdf/2010.11929.pdf> (ViT paper)

“Why replicate machine
learning research papers?”

1. It's fun... and...

```
59 Machine Learning Engineer*
60 -----
61
62 1. Download a paper
63 2. Implement it
64 3. Keep doing this until you have skills
```

- George Hotz, founder of comma.ai

*Machine Learning Engineering also involves building infrastructure around your models/
data preprocessing steps

“What is a machine learning
research paper?”

Anatomy of a research paper*

(and many other kinds of scientific papers)

Section	What is it?
Abstract	An overview/summary of the paper's main findings/contributions.
Introduction	What's the paper's main problem ? And details of previous methods used to try and solve it.
Method	What steps did the researchers take when conducting their research? For example, what model(s), data sources, training setups were used?
Results	What are the outcomes of the paper? If a new type of model or training setup was used, how did the results of findings compare to previous works? (this is where experiment tracking comes in handy)
Conclusion	What are the limitations of the suggested methods? What are some next steps for the research community?
References	What resources/other papers did the researchers look at to build their own body of work?
Appendix	Are there any extra resources/findings to look at that weren't included in any of the above sections?

*This structure is quite fluid. It's more of a general guide than a required outline.

Anatomy of a research paper*

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Published as a conference paper at ICLR 2021

arXiv:2010.11929v2 [cs.CV] 3 Jun 2021

AN IMAGE IS WORTH 16x16 WORDS:
TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE

Alexey Dosovitskiy*,†, Lucas Beyer*, Alexander Kolesnikov*, Dirk Weissenborn*, Xiaohua Zhai*, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, Neil Houlsby*†
*equal technical contribution, †equal advising
Google Research, Brain Team
{adosovitskiy, neilhoulsby}@google.com

ABSTRACT

While the Transformer architecture has become the de-facto standard for natural language processing tasks, its applications to computer vision remain limited. In vision, attention is either applied in conjunction with convolutional networks, or used to replace certain components of convolutional networks while keeping their overall structure in place. We show that this reliance on CNNs is not necessary and a pure transformer applied directly to sequences of image patches can perform very well on image classification tasks. When pre-trained on large amounts of data and transferred to multiple mid-sized or small image recognition benchmarks (ImageNet, CIFAR-100, VTAB, etc.), Vision Transformer (ViT) attains excellent results compared to state-of-the-art convolutional networks while requiring substantially fewer computational resources to train.¹

1 INTRODUCTION

Self-attention-based architectures, in particular Transformers (Vaswani et al., 2017), have become the model of choice in natural language processing (NLP). The dominant approach is to pre-train on a large text corpus and then fine-tune on a smaller task-specific dataset (Devlin et al., 2019). Thanks to Transformers' computational efficiency and scalability, it has become possible to train models of unprecedented size, with over 100B parameters (Brown et al., 2020; Lepikhin et al., 2020). With the models and datasets growing, there is still no sign of saturating performance.

In computer vision, however, convolutional architectures remain dominant (LeCun et al., 1989; Krizhevsky et al., 2012; He et al., 2016). Inspired by NLP successes, multiple works try combining CNN-like architectures with self-attention (Wang et al., 2018; Carion et al., 2020), some replacing the convolutions entirely (Ramachandran et al., 2019; Wang et al., 2020a). The latter models, while theoretically efficient, have not yet been scaled effectively on modern hardware accelerators due to the use of specialized attention patterns. Therefore, in large-scale image recognition, classic ResNet-like architectures are still state of the art (Mahajan et al., 2018; Xie et al., 2020; Kolesnikov et al., 2020).

Source: <https://arxiv.org/pdf/2010.11929.pdf> (ViT paper)

ViT paper

“Where can you find machine
learning research papers?”

Finding machine learning papers (and code)

The screenshot shows the arXiv.org homepage. At the top, there's a search bar with dropdown options for "All fields" and a "Search" button. Below the search bar, there's a "COVID-19 Quick Links" section with a red border containing links to COVID-19 SARS-CoV-2 preprints from arXiv, medRxiv, and bioRxiv. A note below states: "Important: e-prints posted on arXiv are not peer-reviewed by arXiv; they should not be relied upon without context to guide clinical practice or health-related behavior and should not be reported in news media as established information without consulting multiple experts in the field." On the left, there's a sidebar with categories like Physics, Mathematics, Computer Science, and Economics. The main content area shows a list of papers under the "Physics" category.

Source: <https://arxiv.org/>

The screenshot shows a Twitter profile for a user named AK (@akhaliq). The profile picture is a landscape of a snow-covered mountain. The bio reads: "paper tweets, dms are open, ML @Gradio (acc. by @HuggingFace 😊) Science & Technology ⚖ linkedin.com/in/ahsenkhaliq Joined April 2014". The stats show 1,503 Following and 70.3K Followers. A tweet from AK (@akhaliq · 13m ago) is displayed: "Error-Aware Spatial Ensembles for Video Frame Interpolation abs: arxiv.org/abs/2207.12305".

Source: AK Twitter

The screenshot shows a GitHub repository page for "lucidrains/vit-pytorch". The repository has 126 stars, 1.8k forks, and 10.9k issues. The code tab is selected, showing a list of files and their commit history. The repository description is: "Implementation of Vision Transformer, a simple way to achieve SOTA in vision classification with only a single transformer encoder, in Pytorch". It includes tags for computer-vision, transformers, artificial-intelligence, image-classification, and attention-mechanism.

Source: <https://github.com/lucidrains/vit-pytorch>

The screenshot shows the paperswithcode.com website. The top navigation bar includes "Search", "Browse State-of-the-Art", "Datasets", "Methods", and "More". Below the navigation, there are tabs for "Top", "Social", "New", and "Greatest". A section titled "Trending Research" features a project called "Multiface: A Dataset for Neural Face Rendering" by facebookresearch/multiface. The project has 144 stars and 5.19 stars/hour. It includes a "Paper" and "Code" button. Below the project details, there's a link to "Novel View Synthesis on 10,000 People - Human Pose Recognition Data".

Source: <https://paperswithcode.com/>

What we're doing

Replicating the
Vision Transformer
paper (ViT paper)

The screenshot shows a web browser displaying the arXiv.org page for the paper "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale". The page is from Cornell University. The title and authors are listed, along with a summary of the paper's content. A sidebar on the right provides download options and links to related resources.

[2010.11929] An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale

Cornell University

We gratefully acknowledge support from the Simons Foundation and member institutions.

arXiv > cs > arXiv:2010.11929

Search... All fields Search

Help | Advanced Search

Computer Science > Computer Vision and Pattern Recognition

[Submitted on 22 Oct 2020 (v1), last revised 3 Jun 2021 (this version, v2)]

An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, Neil Houlsby

While the Transformer architecture has become the de-facto standard for natural language processing tasks, its applications to computer vision remain limited. In vision, attention is either applied in conjunction with convolutional networks, or used to replace certain components of convolutional networks while keeping their overall structure in place. We show that this reliance on CNNs is not necessary and a pure transformer applied directly to sequences of image patches can perform very well on image classification tasks. When pre-trained on large amounts of data and transferred to multiple mid-sized or small image recognition benchmarks (ImageNet, CIFAR-100, VTAB, etc.), Vision Transformer (ViT) attains excellent results compared to state-of-the-art convolutional networks while requiring substantially fewer computational resources to train.

Download:

- PDF
- Other formats

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Current browse context:
cs.CV
< prev | next >
new | recent | 2010

Change to browse by:
cs
 cs.AI
 cs.LG

References & Citations

- NASA ADS
- Google Scholar
- Semantic Scholar

16 blog links (what is this?)

DBLP – CS Bibliography
listing | bibtex
Alexey Dosovitskiy

Source: [ViT paper](#)

Machine Learning vs. Deep Learning

(common algorithms)

- Random forest
- Gradient boosted models
- Naive Bayes
- Nearest neighbour
- Support vector machine
- ...many more

(since the advent of deep learning these are often referred to as "shallow algorithms")

- Neural networks
- Fully connected neural network
- Convolutional neural network
- Recurrent neural network
- Transformer
- ...many more

What we're focused on building
(with PyTorch)

Structured data ← → Unstructured data

(depending how you represent your problem,
many algorithms can be used for both)

Machine Learning vs. Deep Learning

(common algorithms)



Source: [Photo by John Tubelleza](#)

- Neural networks
- Fully connected neural network
- Convolutional neural network
- Recurrent neural network
- Transformer
- ...many more

What we're focused on building
(with PyTorch)

Unstructured data

Machine Learning vs. Deep Learning

(common algorithms)

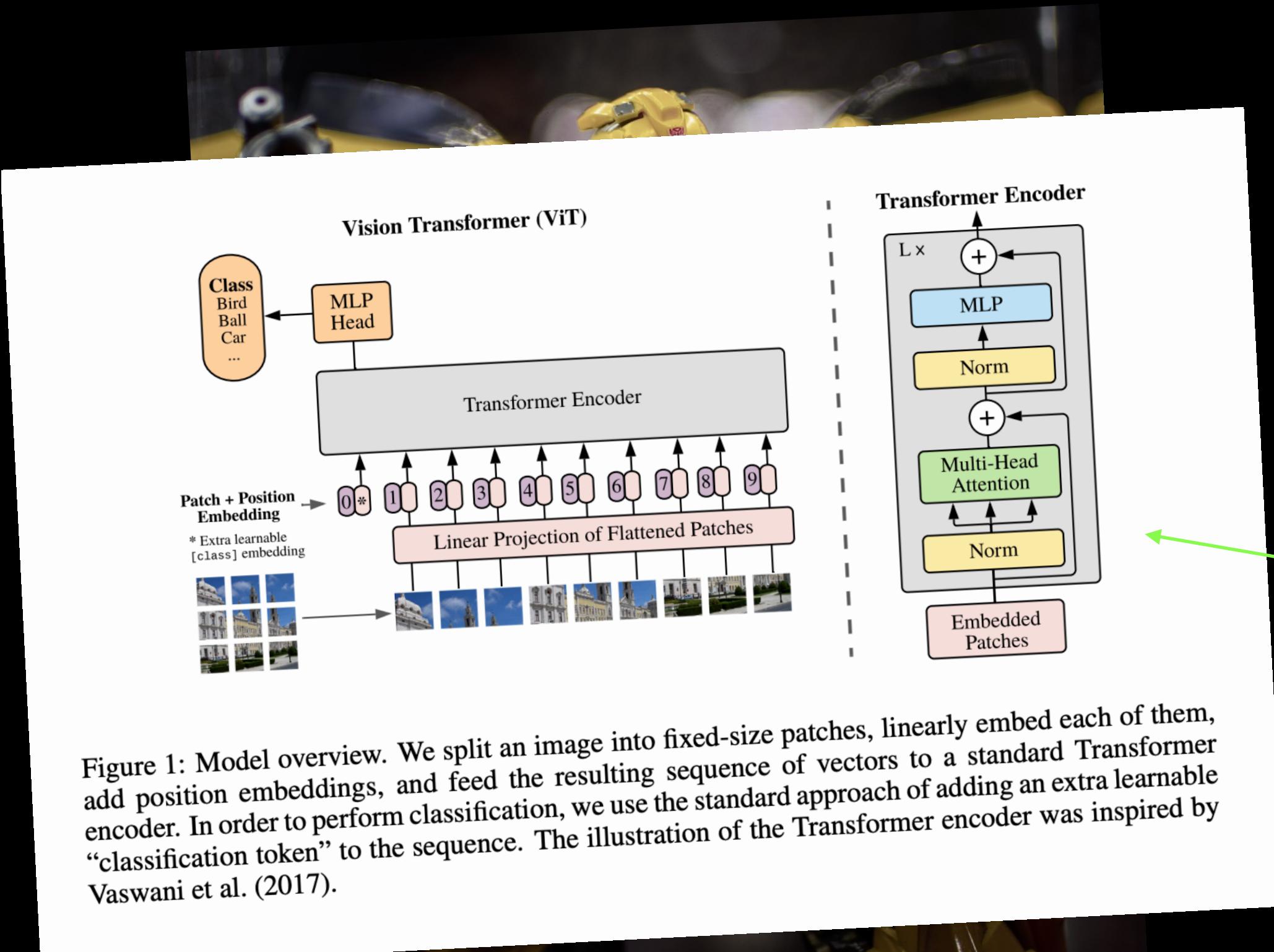


Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable “classification token” to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).



Source: [Photo by John Tubelleza](#)

- Neural networks
- Fully connected neural network
- Convolutional neural network
- Recurrent neural network
- **Transformer**
- ...many more

What we're focused on building
(with PyTorch)

Unstructured data

What we're doing

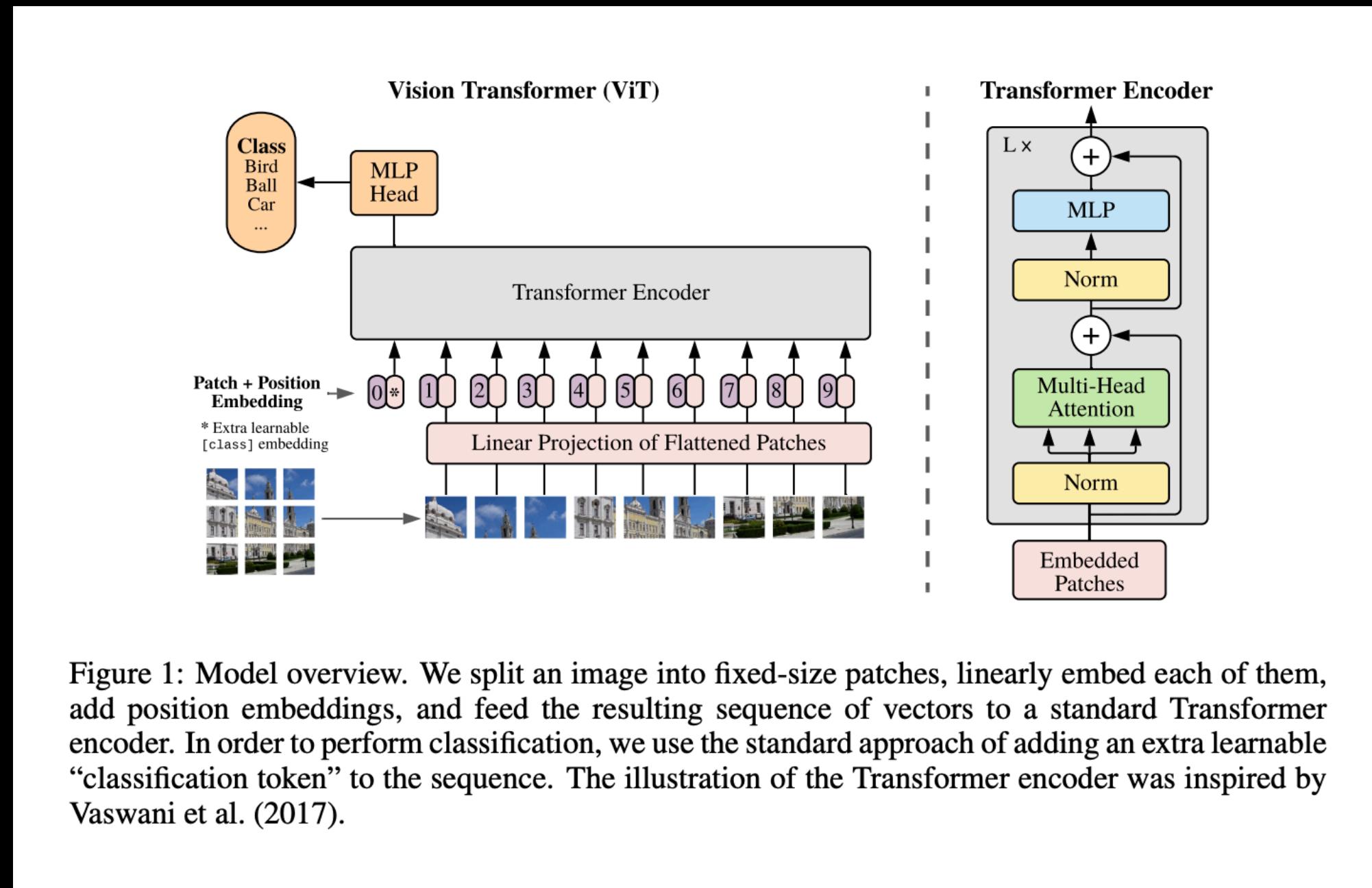
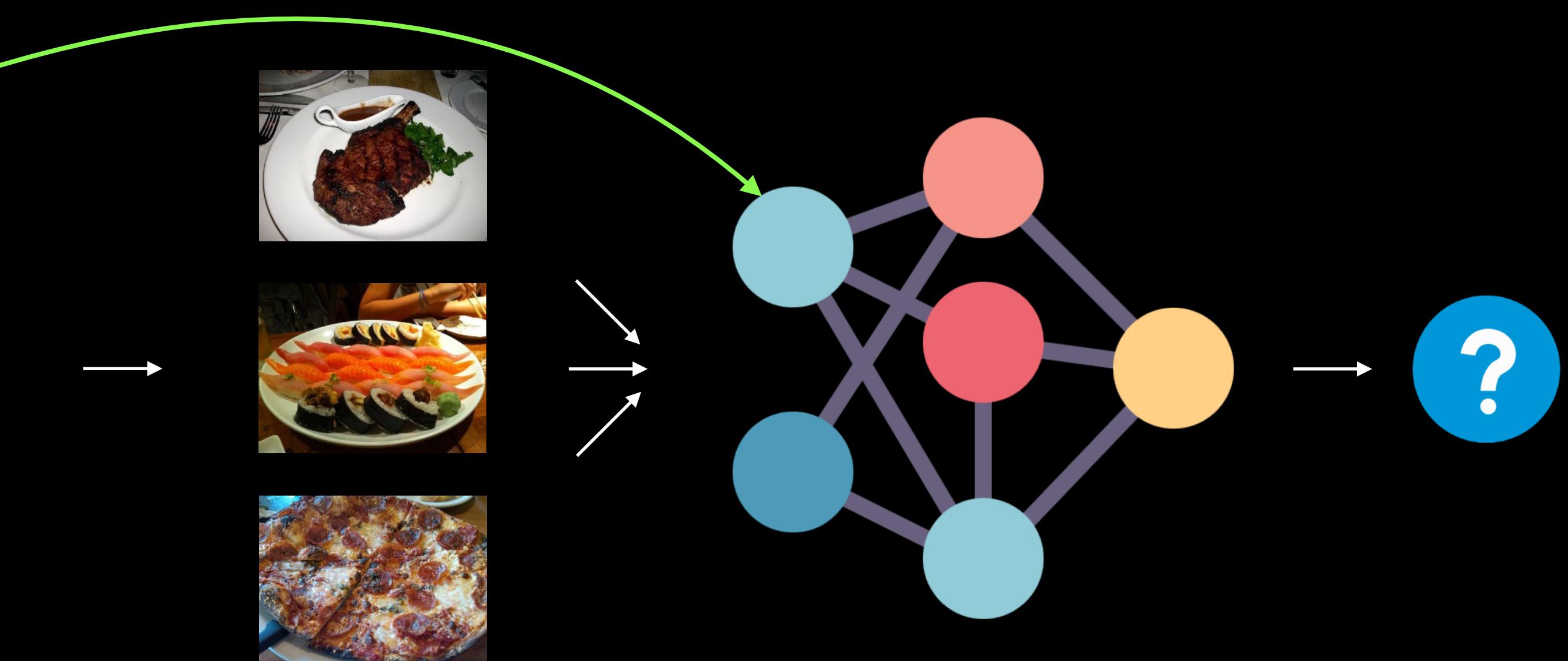


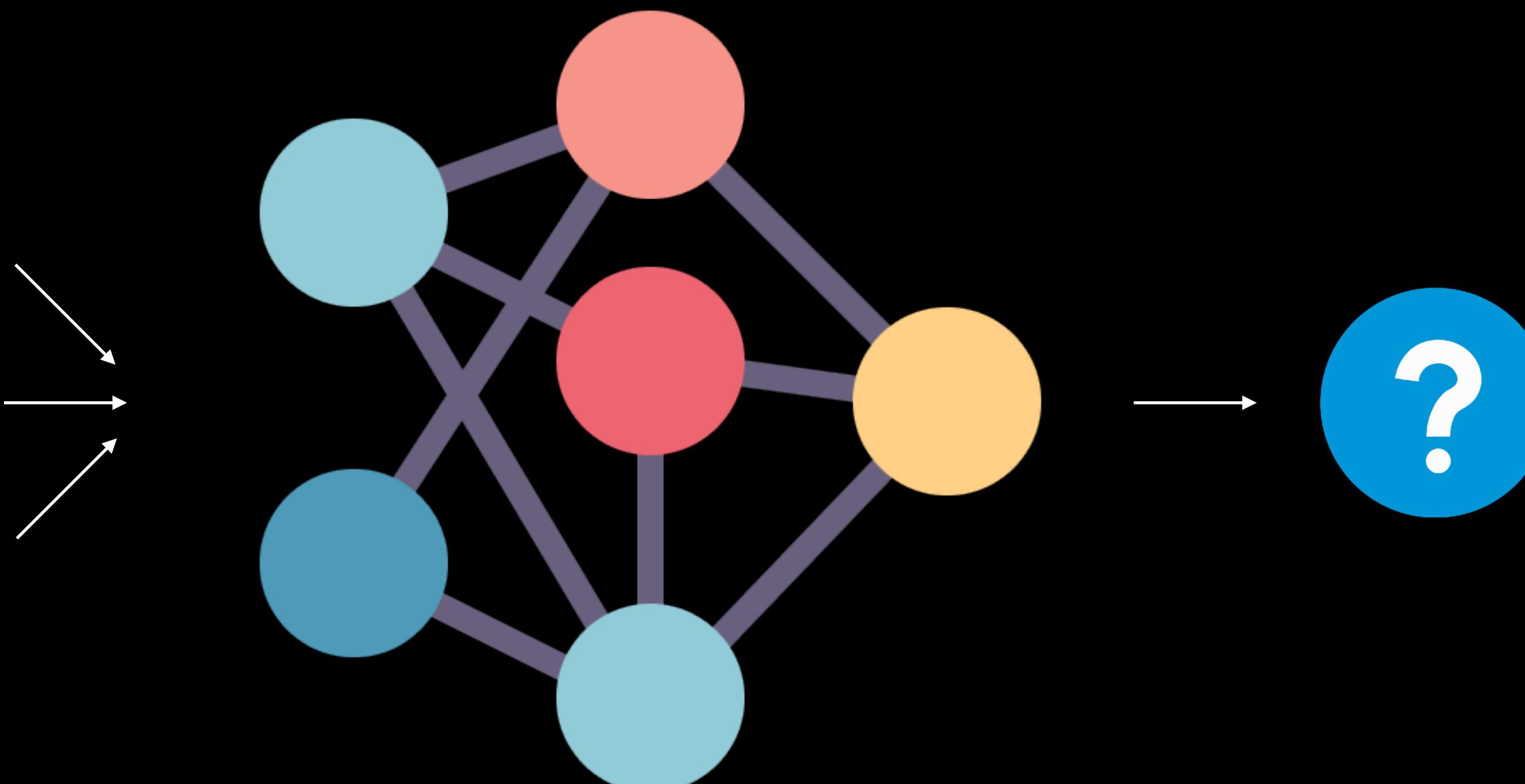
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Vision Transformer architecture

FoodVision Mini

What we're doing



FoodVision Mini 🍕🥩🍣

What we're doing

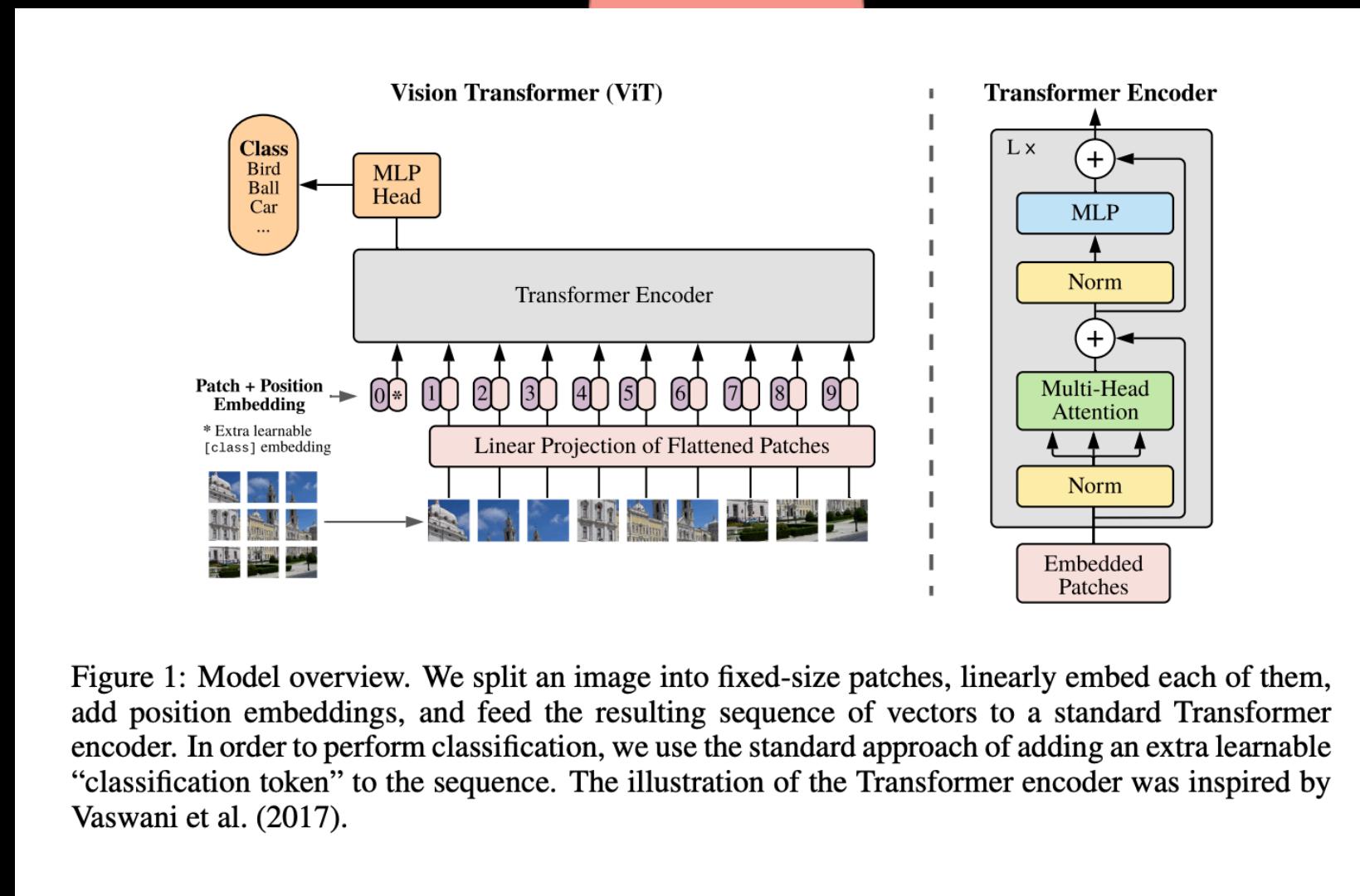
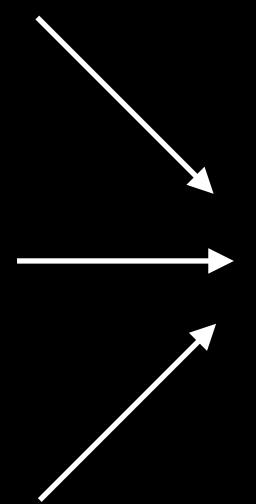
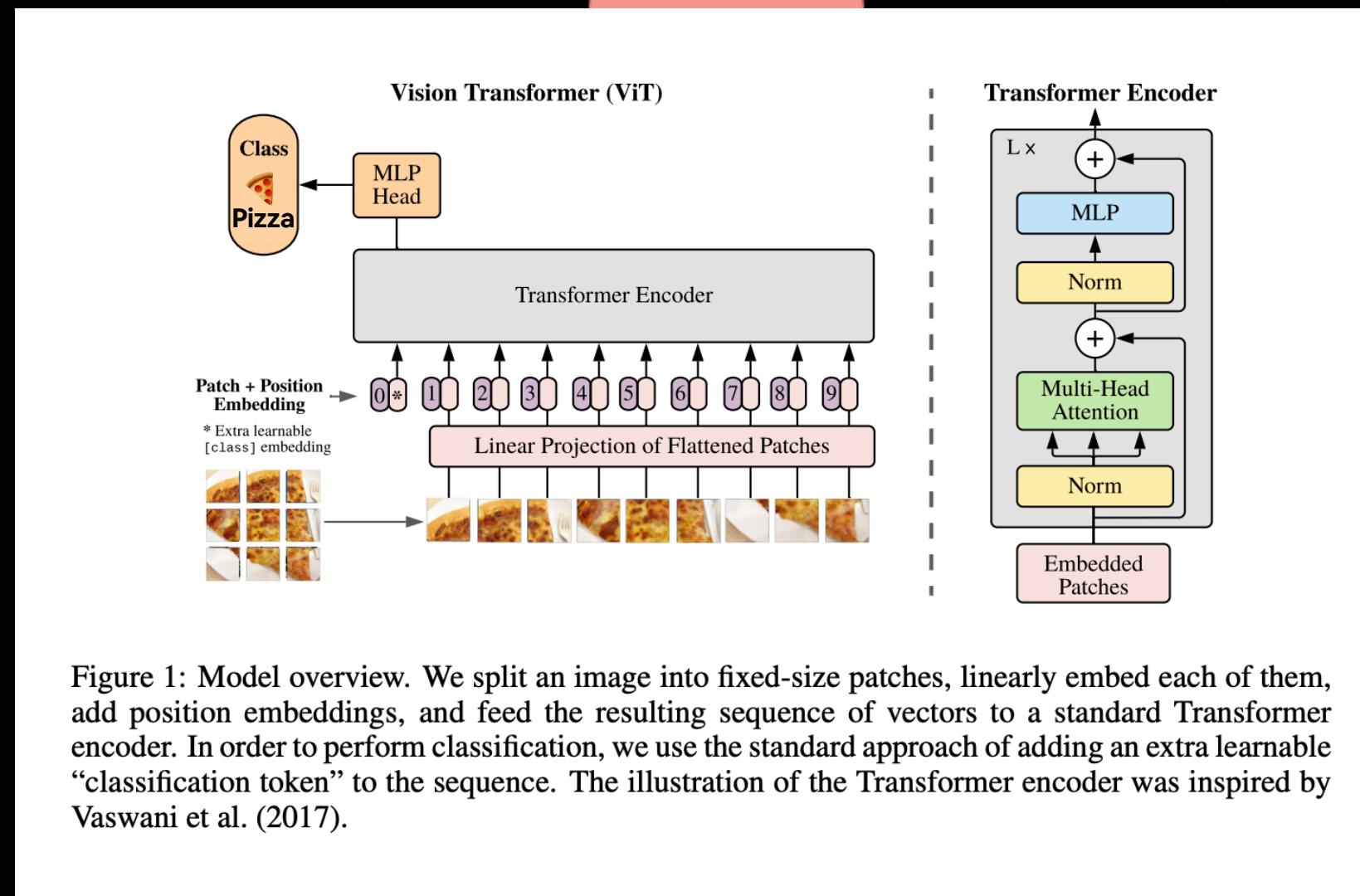
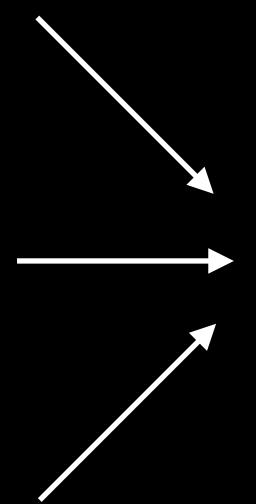


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Source: [ViT paper](#)

FoodVision Mini 🍕🥩🍣

What we're doing



FoodVision Mini 🍕🥩🍣

What we're going to cover

(broadly)

- Getting setup (**importing previously written code**)
- Introduce **machine learning paper replicating** with PyTorch
- **Replicating ViT** for FoodVision Mini 🍕🥩🍣
- Training a **custom ViT**
- Feature extraction with a **pretrained ViT**

(we'll be cooking up lots of code!)

How:



Let's code!

Image size and batch size

Models	Dataset	Epochs	Base LR	LR decay	Weight decay	Dropout
ViT-B/{16,32}	JFT-300M	7	$8 \cdot 10^{-4}$	linear	0.1	0.0
ViT-L/32	JFT-300M	7	$6 \cdot 10^{-4}$	linear	0.1	0.0
ViT-L/16	JFT-300M	7/14	$4 \cdot 10^{-4}$	linear	0.1	0.0
ViT-H/14	JFT-300M	14	$3 \cdot 10^{-4}$	linear	0.1	0.0
R50x{1,2}	JFT-300M	7	10^{-3}	linear	0.1	0.0
R101x1	JFT-300M	7	$8 \cdot 10^{-4}$	linear	0.1	0.0
R152x{1,2}	JFT-300M	7	$6 \cdot 10^{-4}$	linear	0.1	0.0
R50+ViT-B/{16,32}	JFT-300M	7	$8 \cdot 10^{-4}$	linear	0.1	0.0
R50+ViT-L/32	JFT-300M	7	$2 \cdot 10^{-4}$	linear	0.1	0.0
R50+ViT-L/16	JFT-300M	7/14	$4 \cdot 10^{-4}$	linear	0.1	0.0
ViT-B/{16,32}	ImageNet-21k	90	10^{-3}	linear	0.03	0.1
ViT-L/{16,32}	ImageNet-21k	30/90	10^{-3}	linear	0.03	0.1
ViT-*	ImageNet	300	$3 \cdot 10^{-3}$	cosine	0.3	0.1

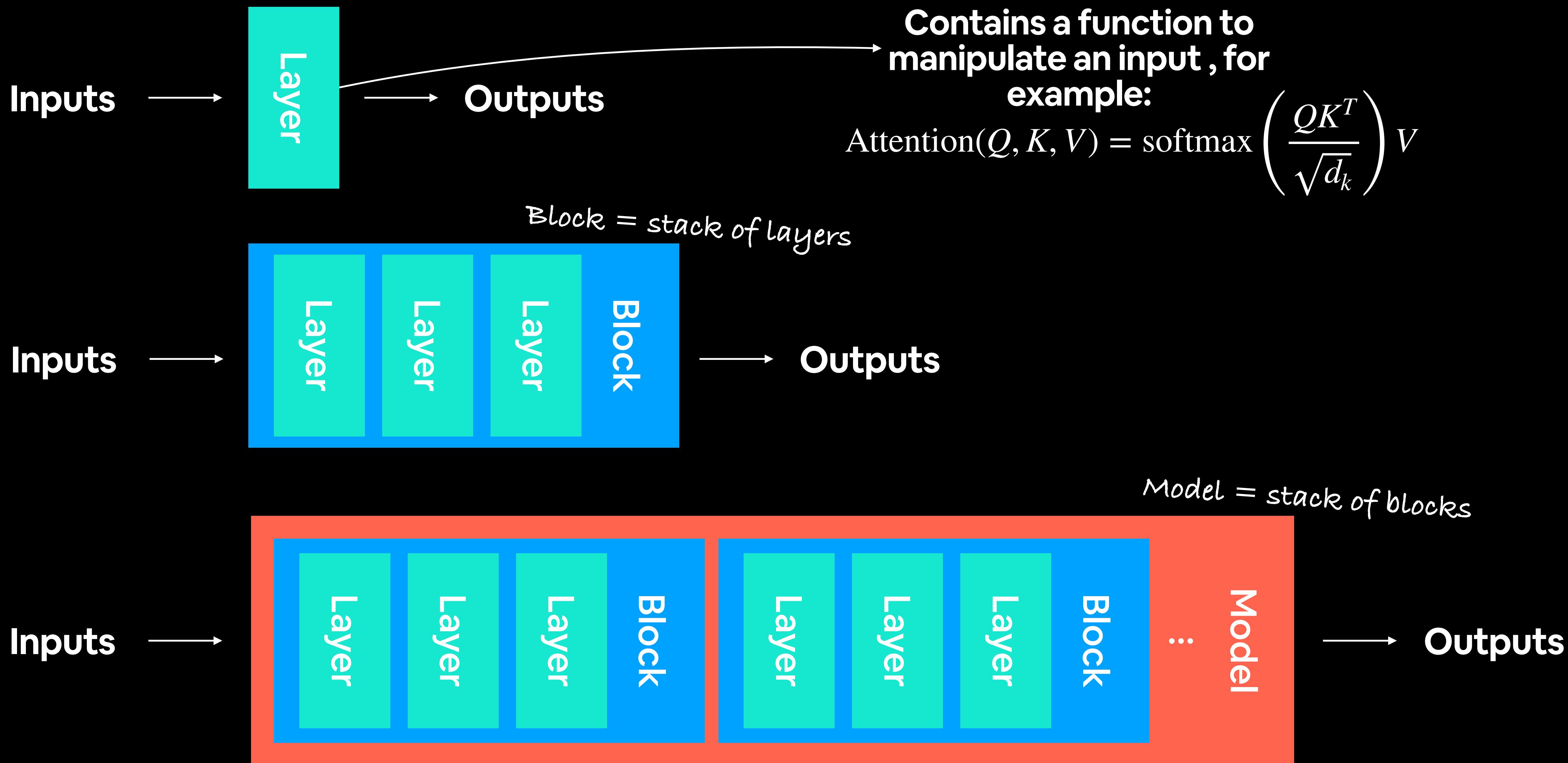
Batch size = 4096

Table 3: Hyperparameters for training. All models are trained with a batch size of 4096 and learning rate warmup of 10k steps. For ImageNet we found it beneficial to additionally apply gradient clipping at global norm 1. Training resolution is 224.

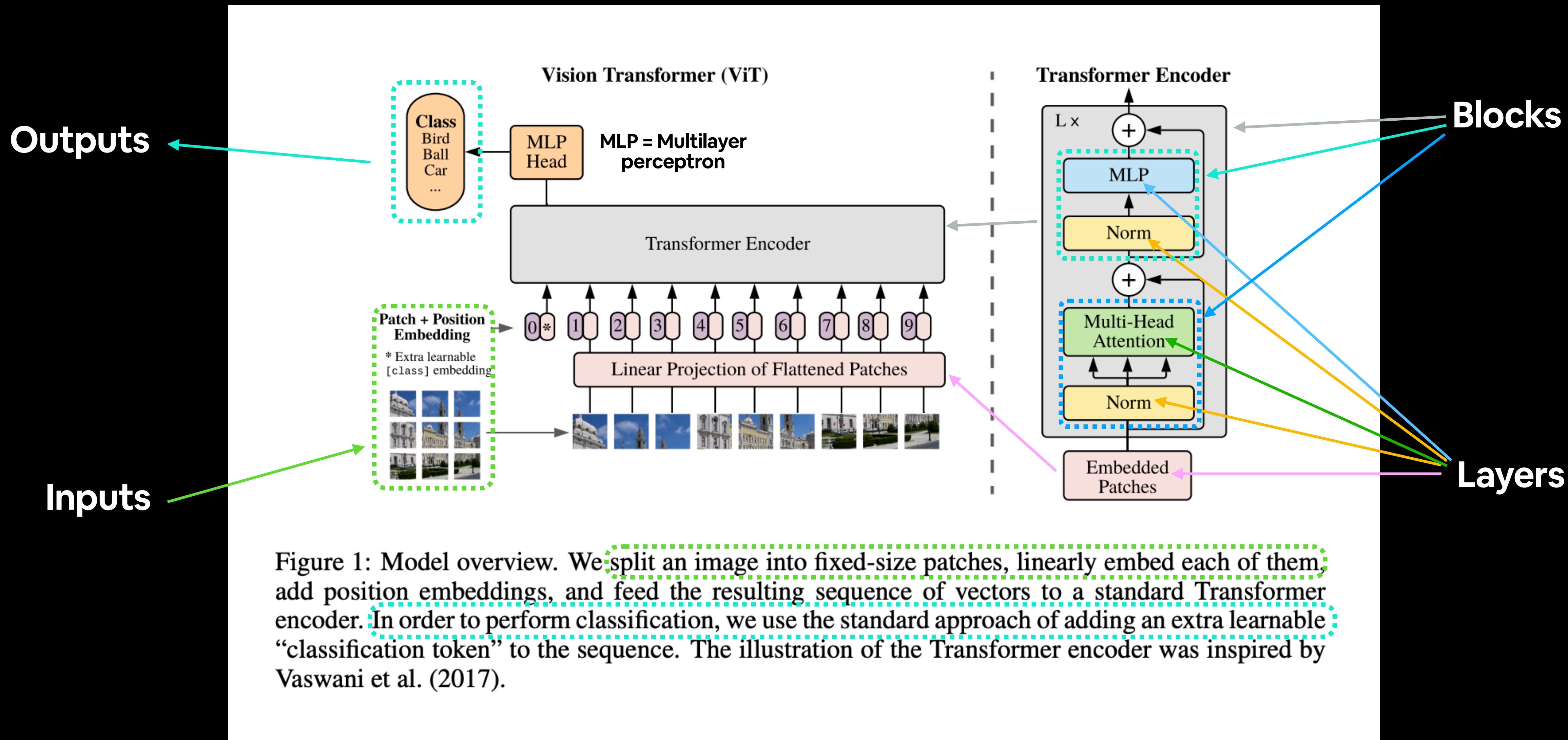
Source: [ViT paper](#)

Image size = 224x224 (height=224, width=224)

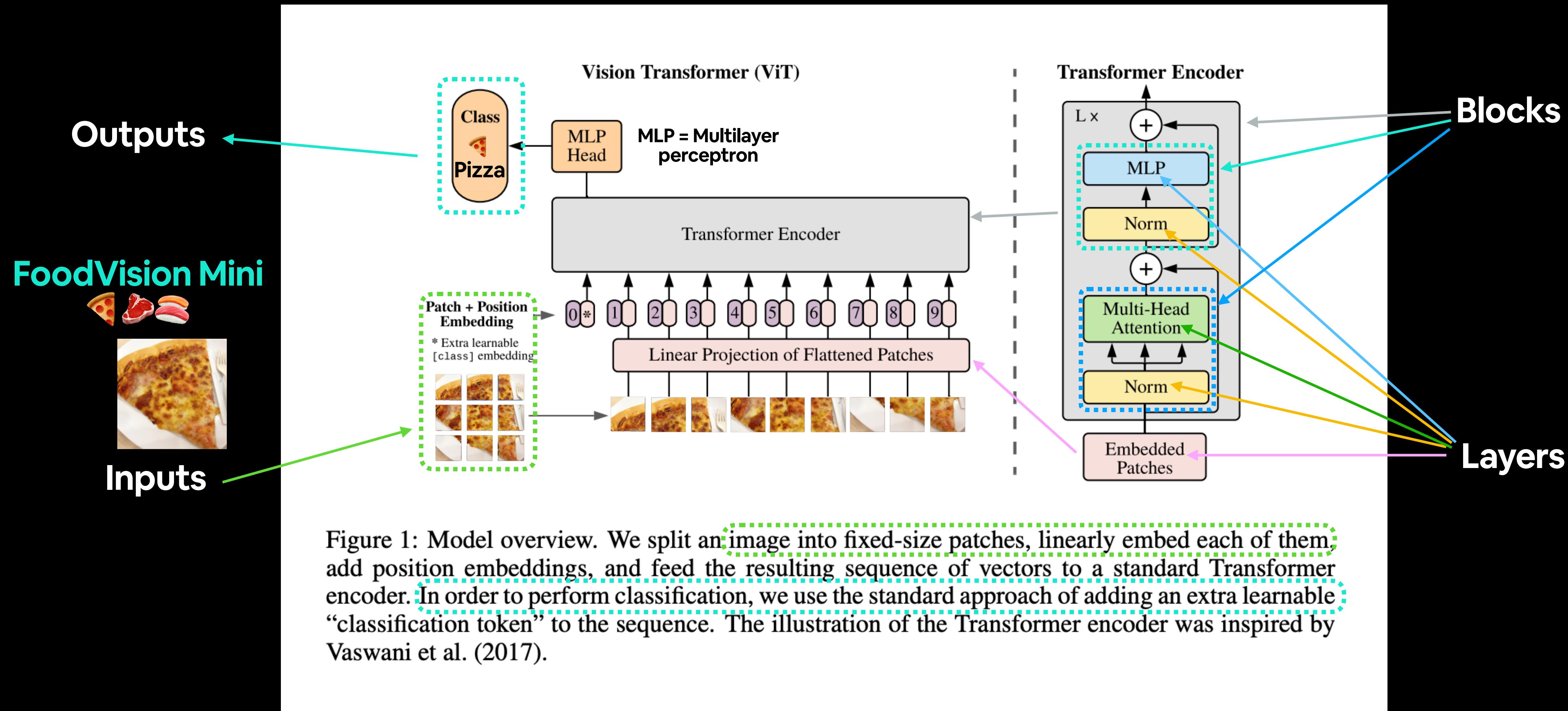
Inputs, outputs, layers and blocks



ViT Overview: Inputs and Outputs



ViT Overview: Inputs and Outputs



Source: ViT paper

ViT Overview: Four Equations

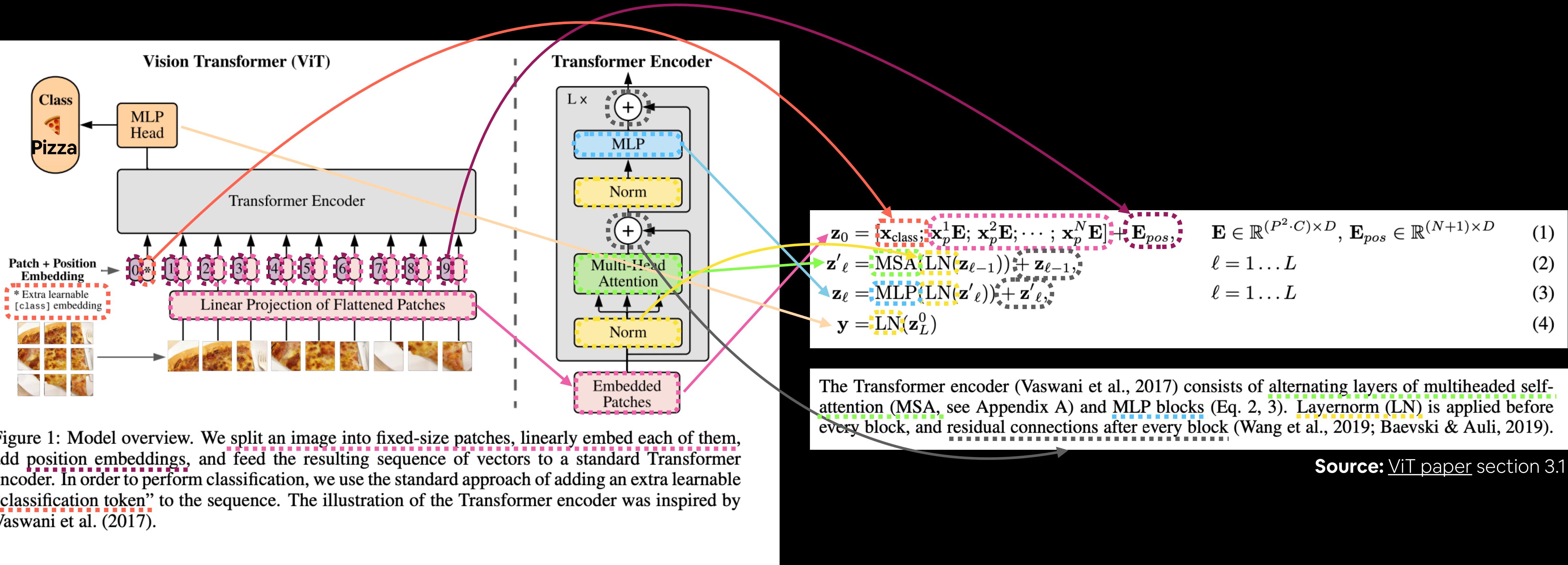


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Source: ViT paper Figure 1

ViT Overview: Workflow

visualize, visualize, visualize!

Original image



FoodVision Mini 🍕🥩🍣

Paper reading tip: math to text

The screenshot shows a web-based note-taking application interface. On the left, there's a sidebar with icons for Snips, PDF, and other functions. The main area has a header "vit-paper-demo" with a timestamp "Updated July 27, 2022 10:42:03 am". Below the header, there's a search bar and a section titled "# Magic!" containing raw mathematical equations. A section titled "\$\$" contains LaTeX code for a multi-head self-attention mechanism. Further down, there's a "Training & Fine-tuning" block with text and a "Attention(Q, K, V) = softmax($\frac{QK^T}{\sqrt{d_k}}$)" equation. At the bottom, there's a note about the model's architecture and a "STANDARD" button.

Magic!

$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{\text{pos}}, \quad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{\text{pos}} \in \mathbb{R}^{(N+1) \times D}$ (1)

$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \quad \ell = 1 \dots L$ (2)

$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad \ell = 1 \dots L$ (3)

$\mathbf{y} = \text{LN}(\mathbf{z}_L^0)$ (4)

$\mathbf{q}, \mathbf{k}, \mathbf{v} = \mathbf{z} \mathbf{U}_{qkv}$

$A = \text{softmax}\left(\mathbf{q}\mathbf{k}^\top / \sqrt{D_h}\right)$

$\text{SA}(\mathbf{z}) = A\mathbf{v}.$

Training & Fine-tuning. We train all models, including ResNets, using Adam (Kingma & Ba, 2015) with $\beta_1 = 0.9$, $\beta_2 = 0.999$, a batch size of 4096 and apply a high weight decay of 0.1, which we found to be useful for training of all models (Appendix D.1 shows that, in contrast to common practices, Adam works slightly better than SGD for ResNets in our setting). We use a linear learning rate warmup strategy (Appendix B.3). For fine-tuning we train with momentum, batch size 512, for all models (see Appendix B.1.1). For ImageNet results in Table 2, we fine-tuned at higher resolution: 512 for ViT-L/16 and 518 for ViT-H/14, and also used Polyak & Juditsky (1992) averaging with a factor of 0.9999 (Ramachandran et al., 2019; Wang et al., 2020b).

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

An overview of the model is depicted in Figure 1. The standard Transformer receives as input a 1D sequence of token embeddings. To handle 2D images, we reshape the image $\mathbf{x} \in \mathbb{R}^{H \times W \times C}$ into a sequence of flattened 2D patches $\mathbf{x}_p \in \mathbb{R}^{N \times (P \cdot C)}$, where (H, W) is the resolution of the original image, C is the number of channels, (P, P) is the resolution of each image patch, and $N = HW/P^2$ is the resulting number of patches, which also serves as the effective input sequence length for the Transformer. The Transformer uses constant latent vector size D through all of its layers, so we flatten the patches and map to D dimensions with a trainable linear projection (Eq. 1). We refer to the output of this projection as the patch embeddings.

Similar to BERT's (Cai et al., 2019) learned learnable embedding to the sequence of embedded patches (\mathbf{z}), whose state is the output of the Transformer encoder (\mathbf{z}') we use as the image representation \mathbf{y} (Eq. 4). Both during pre-training and fine-tuning, a classification head is attached to \mathbf{z}' . The classification head is implemented by a MLP with one hidden layer at pre-training time and by a single linear layer at fine-tuning time.

Position embeddings are added to the patch embeddings to retain positional information. We use standard learnable 1D position embeddings, since we have not observed significant performance gains from more advanced 2D-aware position embeddings (Appendix D.4). The resulting sequence of embedding vectors serves as input to the encoders.

The Transformer encoder (Vaswani et al., 2017) consists of alternating layers of multiheaded self-attention (MSA, see Appendix A) and MLP blocks (Eq. 2, 3). Layernorm (LN) is applied before every block, and residual connections after every block (Wang et al., 2019; Baevski & Auli, 2019).

Magic!

$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{\text{pos}}, \quad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{\text{pos}} \in \mathbb{R}^{(N+1) \times D}$

$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \quad \ell = 1 \dots L$

$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad \ell = 1 \dots L$

$\mathbf{y} = \text{LN}(\mathbf{z}_L^0)$

Source: mathpix.com, see a [live demo](#)

Equation 1: The Patch Embedding

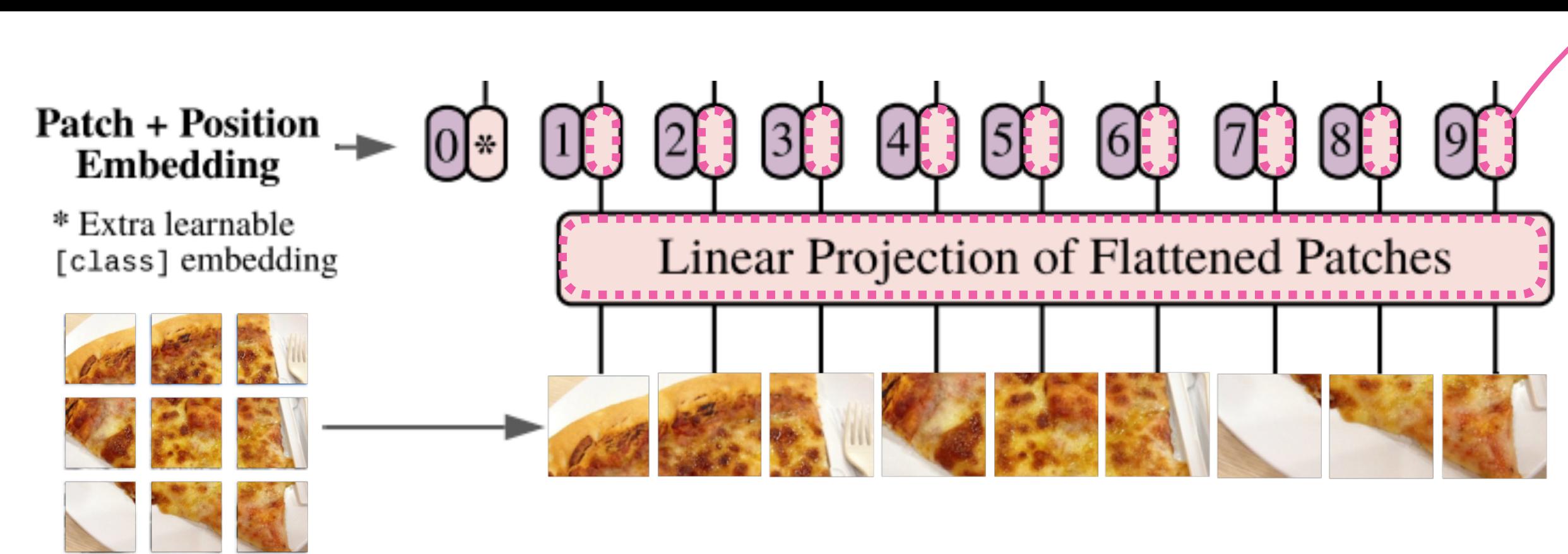


Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable “classification token” to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).

Image size = (H, W, C) -> (N_Patches, (P² • C))

For example, patch size = 16 (ViT-Base):
 $(224, 224, 3) \rightarrow (196, 768)$

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}, \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{\text{pos}}, \quad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{\text{pos}} \in \mathbb{R}^{(N+1) \times D} \quad (1)$$

$$\ell = 1 \dots L \quad (2)$$

$$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \quad \ell = 1 \dots L \quad (3)$$

$$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad \ell = 1 \dots L \quad (4)$$

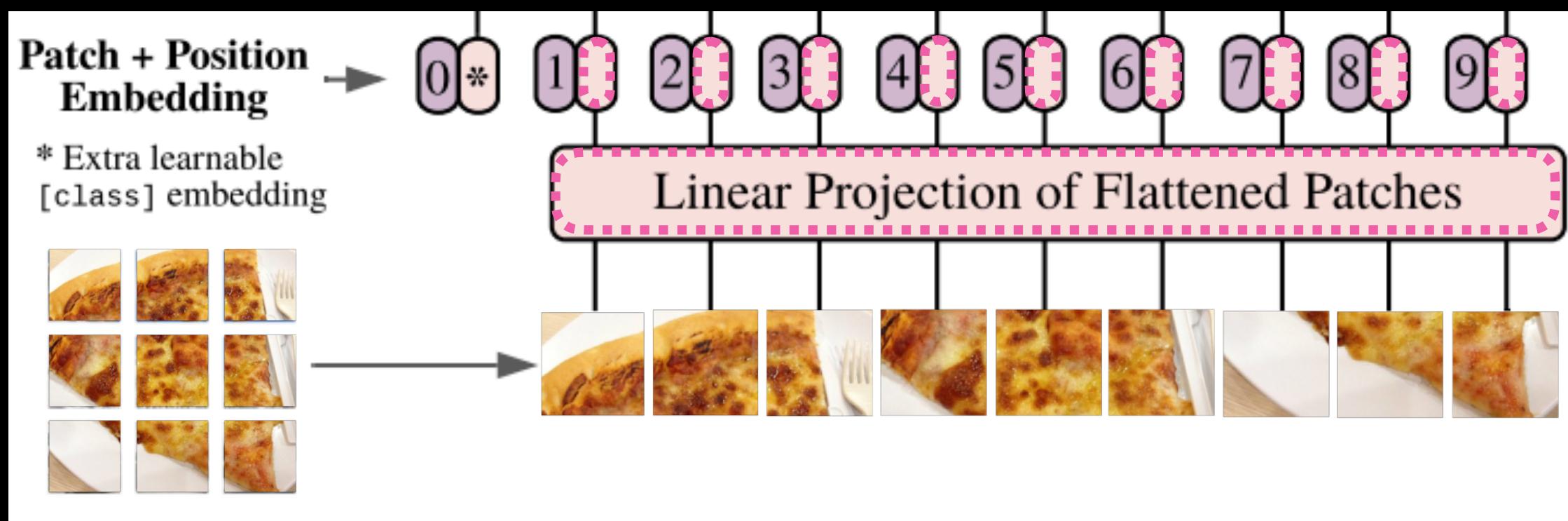
$$\mathbf{y} = \text{LN}(\mathbf{z}_L^0) \quad (4)$$

3.1 VISION TRANSFORMER (ViT)

An overview of the model is depicted in Figure 1. The standard Transformer receives as input a 1D sequence of token embeddings. To handle 2D images, we reshape the image $\mathbf{x} \in \mathbb{R}^{H \times W \times C}$ into a sequence of flattened 2D patches $\mathbf{x}_p \in \mathbb{R}^{N \times (P^2 \cdot C)}$, where (H, W) is the resolution of the original image, C is the number of channels, (P, P) is the resolution of each image patch, and $N = HW/P^2$ is the resulting number of patches, which also serves as the effective input sequence length for the Transformer. The Transformer uses constant latent vector size D through all of its layers, so we flatten the patches and map to D dimensions with a trainable linear projection (Eq. 1). We refer to the output of this projection as the patch embeddings.

Embedding size (D) = 768 (ViT-Base)

Equation 1: The Patch Embedding



$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{\text{pos}}, \quad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{\text{pos}} \in \mathbb{R}^{(N+1) \times D} \quad (1)$$

$$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \quad \ell = 1 \dots L \quad (2)$$

$$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad \ell = 1 \dots L \quad (3)$$

$$\mathbf{y} = \text{LN}(\mathbf{z}_L^0) \quad (4)$$

```

# 1. Create a class which subclasses nn.Module
class PatchEmbedding(nn.Module):
    """Turns a 2D input image into a 1D sequence learnable embedding vector.

    Args:
        in_channels (int): Number of color channels for the input images. Defaults to 3.
        patch_size (int): Size of patches to convert input image into. Defaults to 16.
        embedding_dim (int): Size of embedding to turn image into. Defaults to 768.
    """

# 2. Initialize the class with appropriate variables
def __init__(self,
             in_channels:int=3,
             patch_size:int=16,
             embedding_dim:int=768): # same as ViT-Base
    super().__init__()

# 3. Create a layer to turn an image into patch embeddings
    self.patcher = nn.Conv2d(in_channels=in_channels,
                           out_channels=embedding_dim,
                           kernel_size=patch_size,
                           stride=patch_size,
                           padding=0)

# 4. Create a layer to flatten the patch feature maps into a single dimension
    self.flatten = nn.Flatten(start_dim=2, # only flatten the feature map dimensions
                             end_dim=3)

# 5. Define the forward method
def forward(self, x):
    x_patched = self.patcher(x)
    x_flattened = self.flatten(x_patched)

# 6. Make sure the output shape has the right order
    return x_flattened.permute(0, 2, 1) # [batch_size, P^2•C, N] -> [batch_size, N, P^2•C]

```

Equation 1: The Class Token

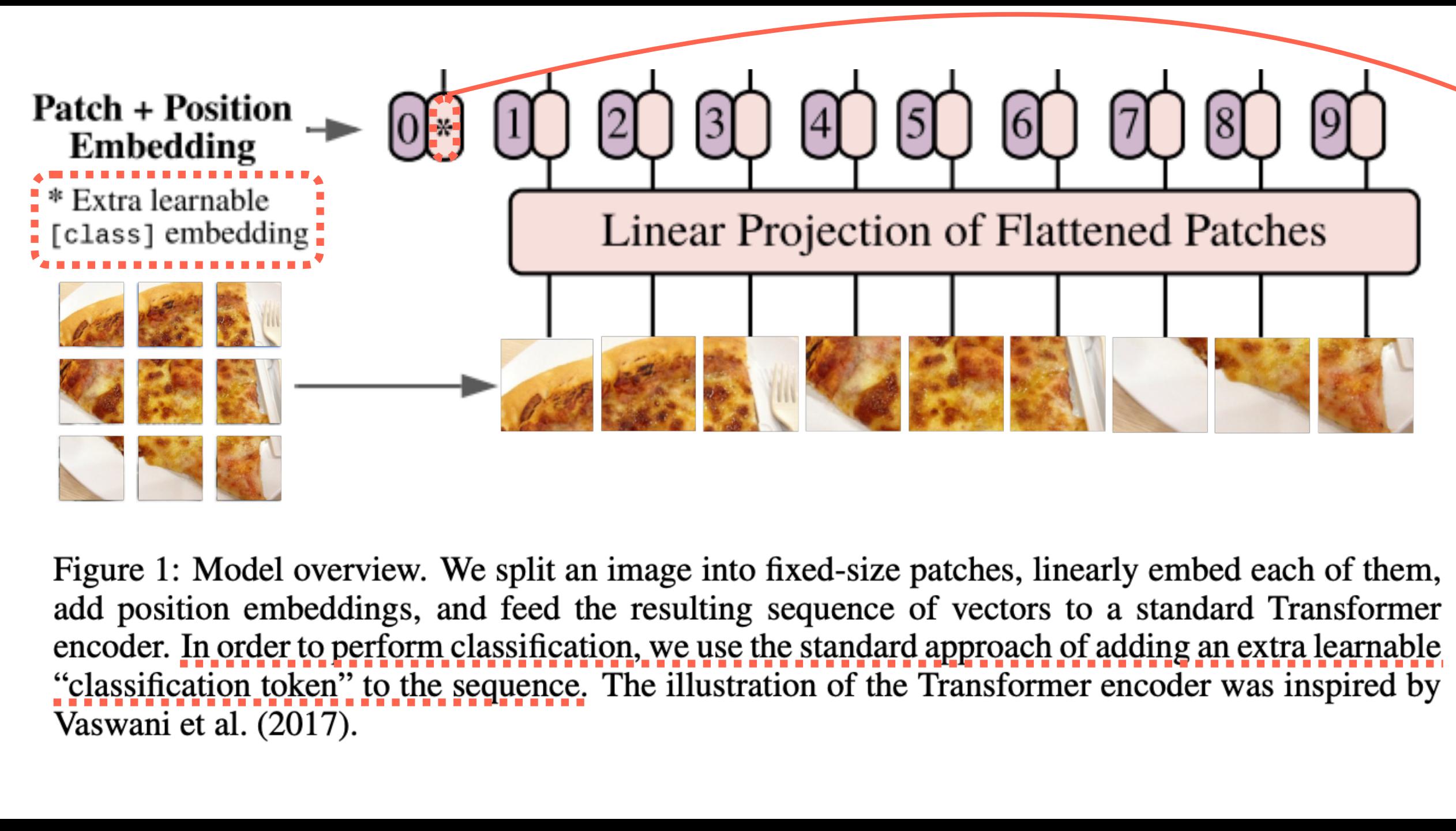


Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable “classification token” to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{\text{pos}}, \quad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{\text{pos}} \in \mathbb{R}^{(N+1) \times D} \quad (1)$$

$$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \quad \ell = 1 \dots L \quad (2)$$

$$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad \ell = 1 \dots L \quad (3)$$

$$\mathbf{y} = \text{LN}(\mathbf{z}_L^0) \quad (4)$$

Similar to BERT’s [class] token, we prepend a learnable embedding to the sequence of embedded patches ($\mathbf{z}_0^0 = \mathbf{x}_{\text{class}}$), whose state at the output of the Transformer encoder (\mathbf{z}_L^0) serves as the image representation \mathbf{y} (Eq. 4). Both during pre-training and fine-tuning, a classification head is attached to \mathbf{z}_L^0 . The classification head is implemented by a MLP with one hidden layer at pre-training time and by a single linear layer at fine-tuning time.

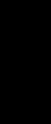
Prepend a **learnable class embedding** token to
the 0 index of the patch embedding

Equation 1: The Class Token

Sequence of patch embeddings

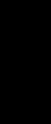
```
tensor([[[ -0.3714,  0.0556, -0.1053, ...,  0.2598, -0.1740,  0.1473],  
       [-0.4294,  0.0788, -0.1078, ...,  0.2671, -0.1797,  0.1644],  
       [-0.4774,  0.0965, -0.1198, ...,  0.3465, -0.1918,  0.1432],  
       ...,  
       [-0.1749,  0.0247, -0.0610, ...,  0.1185, -0.0448,  0.0451],  
       [-0.1679,  0.0264, -0.0745, ...,  0.1182, -0.0693,  0.0623],  
       [-0.0631, -0.0043, -0.0612, ...,  0.0553, -0.0460,  0.0837]]],  
grad_fn=<PermuteBackward0>)
```

Shape: [1, 196, 786], [batch_size, number_of_patches, embedding_dimension]



Create learnable class token and prepend it to patch embeddings

```
# Create the class token embedding  
class_token = nn.Parameter(torch.ones(batch_size, 1, embedding_dimension),  
                           requires_grad=True) # make embedding learnable  
  
# Add the class token embedding to the front of the patch embedding  
patch_embedded_image_with_class_embedding = torch.cat((class_token, patch_embedded_image),  
                                                       dim=1) # concat on first dimension
```



Patch embeddings with learnable class token

```
tensor([[ 1.0000,  1.0000,  1.0000, ...,  1.0000,  1.0000,  1.0000],  
       [-0.3714,  0.0556, -0.1053, ...,  0.2598, -0.1740,  0.1473],  
       [-0.4294,  0.0788, -0.1078, ...,  0.2671, -0.1797,  0.1644],  
       ...,  
       [-0.1749,  0.0247, -0.0610, ...,  0.1185, -0.0448,  0.0451],  
       [-0.1679,  0.0264, -0.0745, ...,  0.1182, -0.0693,  0.0623],  
       [-0.0631, -0.0043, -0.0612, ...,  0.0553, -0.0460,  0.0837]]],  
grad_fn=<CatBackward0>)
```

Learnable class token

prepend

Shape: [1, 197, 786], [batch_size, number_of_patches + class_token, embedding_dimension]

Equation 1: The Position Embedding

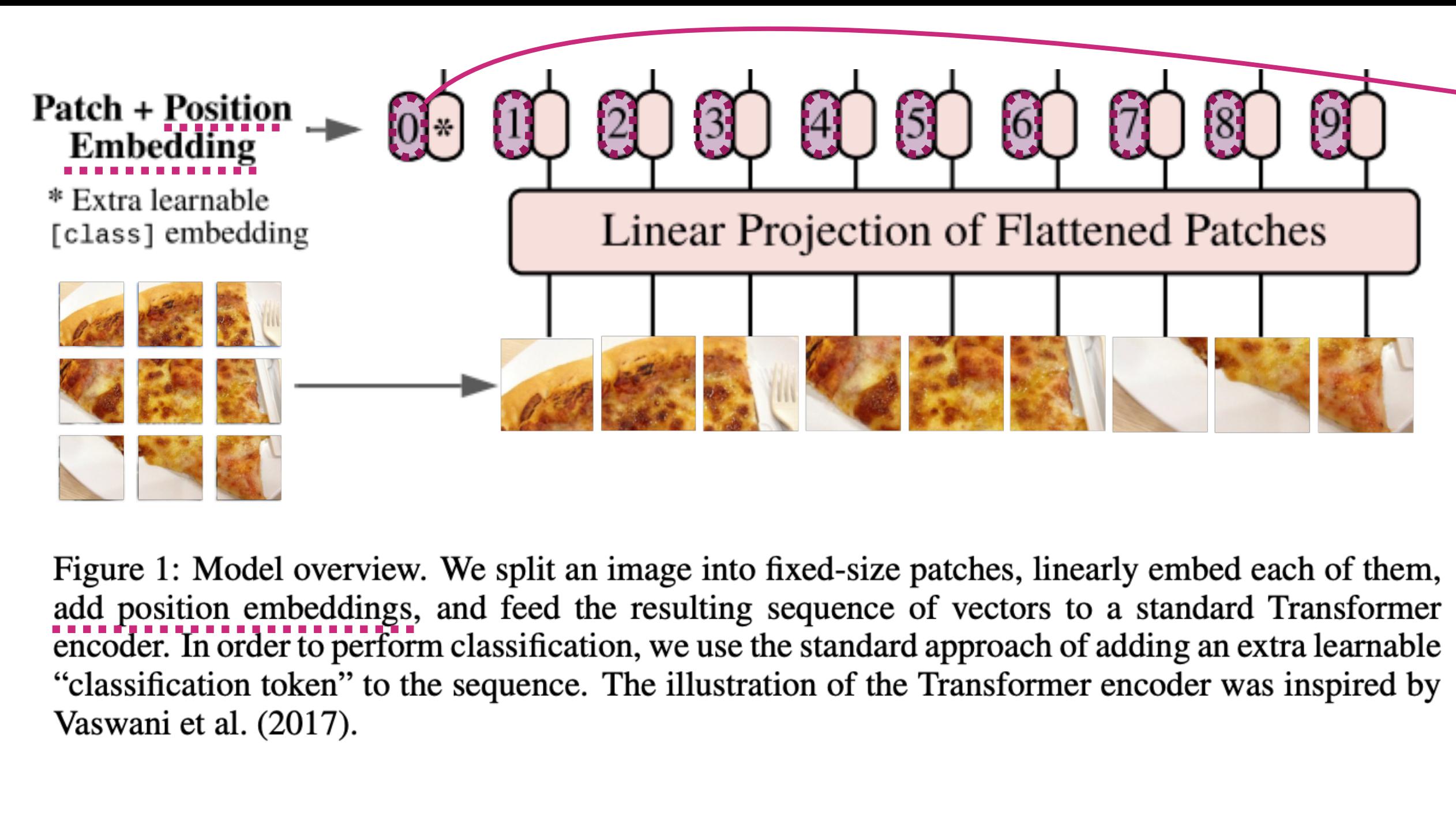


Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable “classification token” to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).

Position Embeddings Shape:
[num_patches+1, embedding_dimension]
(+1 is for the class_token)

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{\text{pos}}, \quad (1)$$

$$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \quad (2)$$

$$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad (3)$$

$$\mathbf{y} = \text{LN}(\mathbf{z}_L^0) \quad (4)$$

Position embeddings are added to the patch embeddings to retain positional information. We use standard learnable 1D position embeddings, since we have not observed significant performance gains from using more advanced 2D-aware position embeddings (Appendix D.4). The resulting sequence of embedding vectors serves as input to the encoder.

Add a **learnable 1D set of position embeddings**
to [class_token, patch embedding]

Equation 1: The Position Embedding

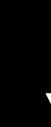
Patch embeddings with learnable class token

Create position embeddings and add to patch embeddings with learnable class token

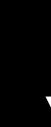
Patch embeddings with learnable class token and position embeddings

```
tensor([[ 1.0000,  1.0000,  1.0000, ...,  1.0000,  1.0000,  1.0000],  
       [-0.3714,  0.0556, -0.1053, ...,  0.2598, -0.1740,  0.1473],  
       [-0.4294,  0.0788, -0.1078, ...,  0.2671, -0.1797,  0.1644],  
       ...,  
       [-0.1749,  0.0247, -0.0610, ...,  0.1185, -0.0448,  0.0451],  
       [-0.1679,  0.0264, -0.0745, ...,  0.1182, -0.0693,  0.0623],  
       [-0.0631, -0.0043, -0.0612, ...,  0.0553, -0.0460,  0.0837]]],  
grad_fn=<CatBackward0>)
```

Shape: [1, 197, 786], [batch_size, number_of_patches + class_token, embedding_dimension]



```
# Create the learnable 1D position embedding  
position_embedding = nn.Parameter(torch.ones(1, number_of_patches+1, embedding_dimension),  
                                requires_grad=True) # make sure it's learnable  
  
# Add the position embedding to the patch and class token embedding  
patch_and_position_embedding = patch_embedded_image_with_class_embedding + position_embedding
```



```
tensor([[ [2.0000, 2.0000, 2.0000, ..., 2.0000, 2.0000, 2.0000],  
          [0.6286, 1.0556, 0.8947, ..., 1.2598, 0.8260, 1.1473],  
          [0.5706, 1.0788, 0.8922, ..., 1.2671, 0.8203, 1.1644],  
          ...,  
          [0.8251, 1.0247, 0.9390, ..., 1.1185, 0.9552, 1.0451],  
          [0.8321, 1.0264, 0.9255, ..., 1.1182, 0.9307, 1.0623],  
          [0.9369, 0.9957, 0.9388, ..., 1.0553, 0.9540, 1.0837]]],  
grad_fn=<AddBackward0>)
```

values all changed thanks to position embeddings

Shape: [1, 197, 786], [batch_size, number_of_patches + class_token, embedding_dimension]

Equation 1: Putting it all together

```

# 1. Set patch size
patch_size = 16

# 2. Print shape of original image tensor and get the image dimensions
print(f"Image tensor shape: {image.shape}")
height, width = image.shape[1], image.shape[2]

# 3. Get image tensor and add batch dimension
x = image.unsqueeze(0)
print(f"Input image with batch dimension shape: {x.shape}")

# 4. Create patch embedding layer
patch_embedding_layer = PatchEmbedding(in_channels=3, # number of color channels in image
                                         patch_size=patch_size,
                                         embedding_dim=768) # from Table 1 for ViT-Base

# 5. Pass image through patch embedding layer
patch_embedding = patch_embedding_layer(x)
print(f"Patch embedding shape: {patch_embedding.shape}")

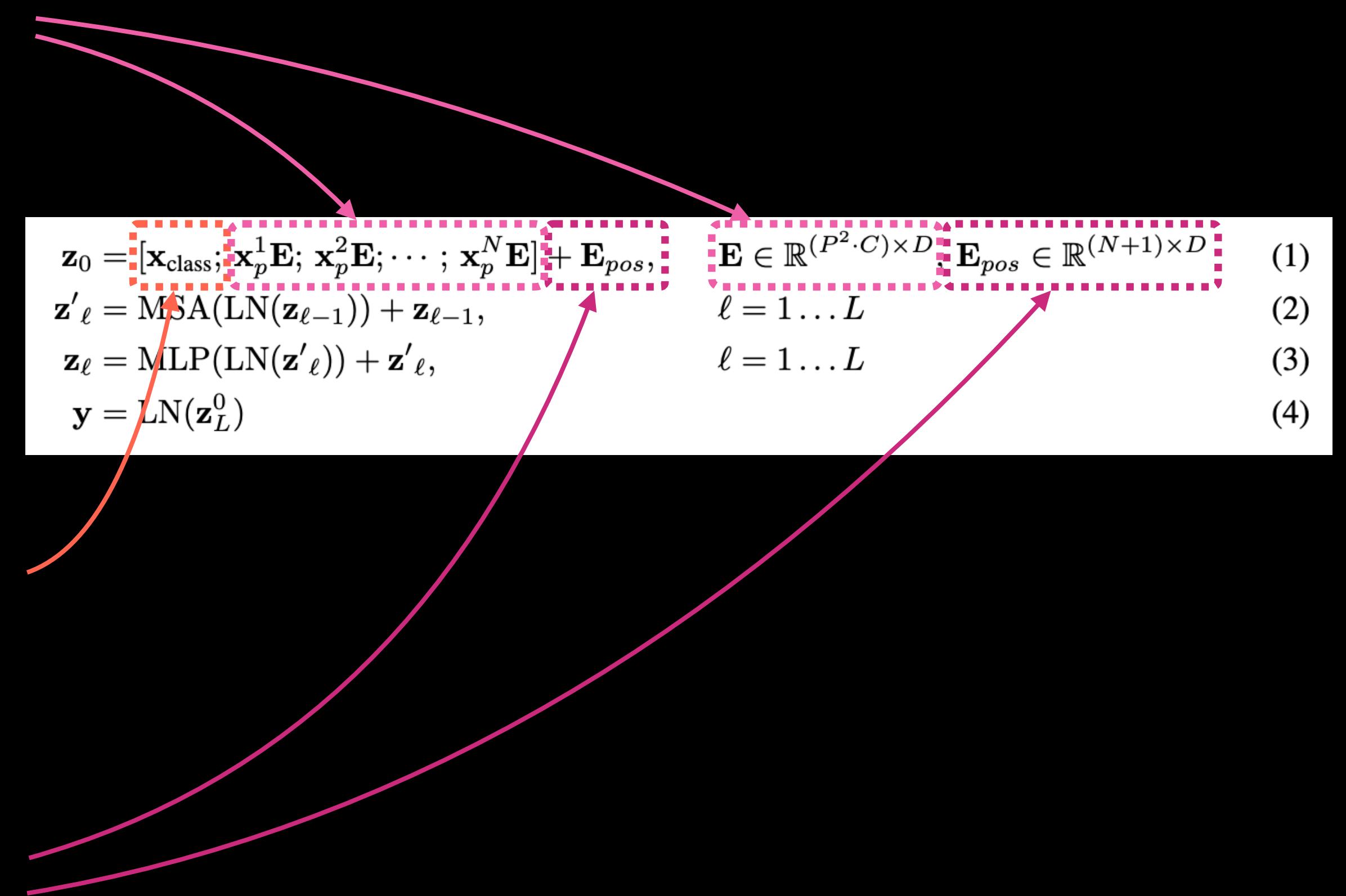
# 6. Create class token embedding
batch_size = patch_embedding.shape[0]
embedding_dimension = patch_embedding.shape[-1]
class_token = nn.Parameter(torch.ones(batch_size, 1, embedding_dimension),
                           requires_grad=True) # make sure it's learnable
print(f"Class token embedding shape: {class_token.shape}")

# 7. Prepend class token embedding to patch embedding
patch_embedding_class_token = torch.cat((class_token, patch_embedding), dim=1)
print(f"Patch embedding with class token shape: {patch_embedding_class_token.shape}")

# 8. Create position embedding
number_of_patches = int((height * width) / patch_size**2)
position_embedding = nn.Parameter(torch.ones(1, number_of_patches+1, embedding_dimension),
                                 requires_grad=True) # make sure it's learnable

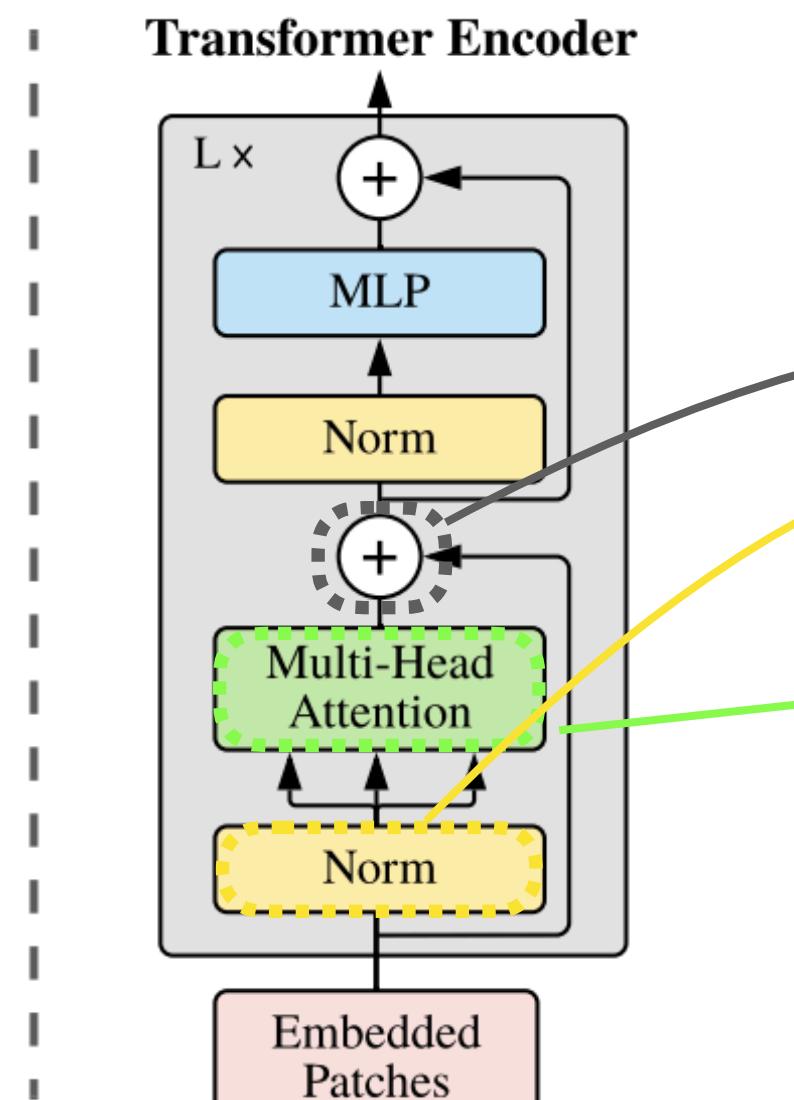
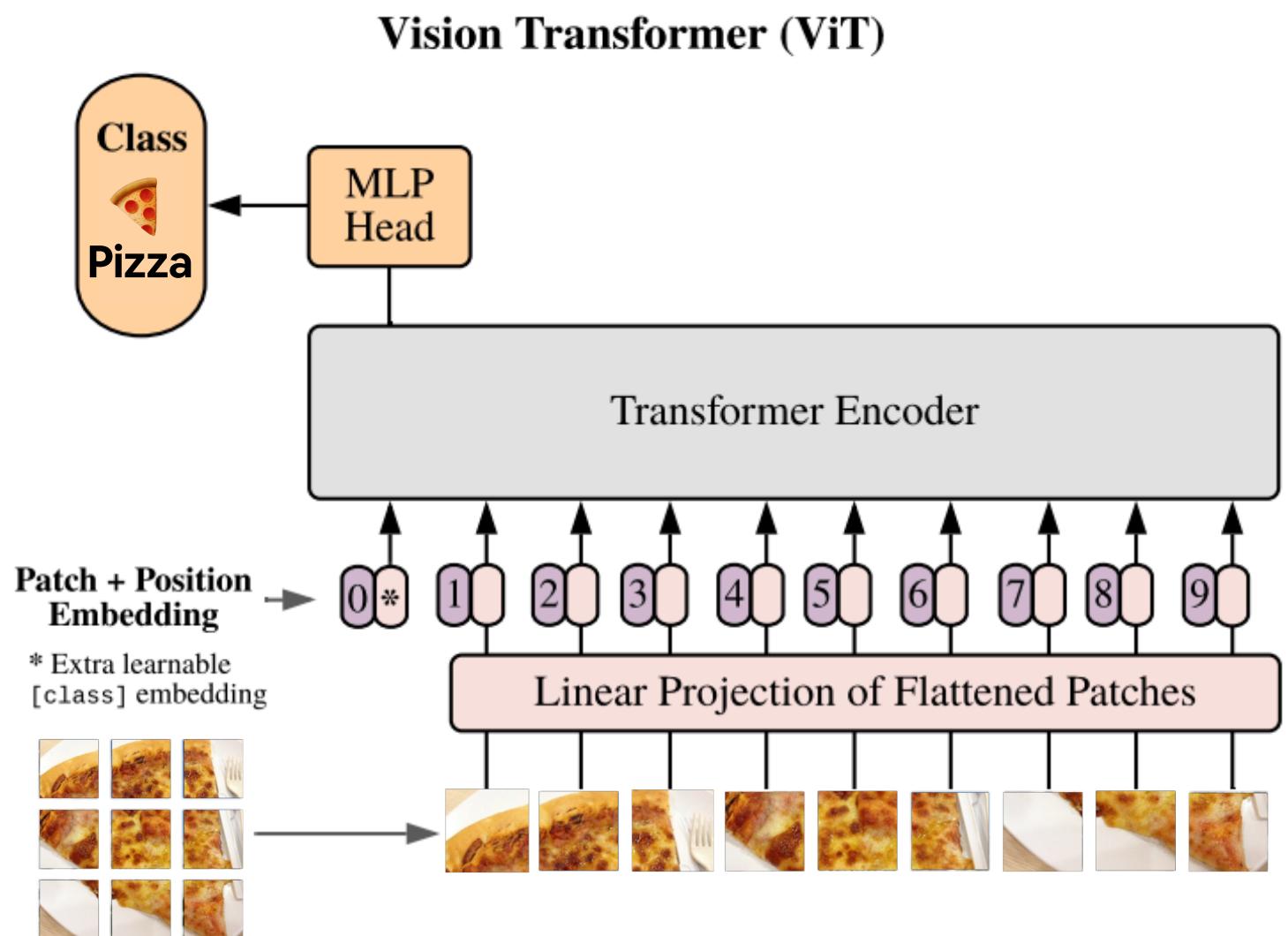
# 9. Add position embedding to patch embedding with class token
patch_and_position_embedding = patch_embedding_class_token + position_embedding
print(f"Patch and position embedding shape: {patch_and_position_embedding.shape}")

```



Equation 2: The MSA Block

MSA = Multi-Head Self Attention



Equation 2 = “MSA block”

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{\text{pos}}, \quad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{\text{pos}} \in \mathbb{R}^{(N+1) \times D} \quad (1)$$

$$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \quad \ell = 1 \dots L \quad (2)$$

$$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad \ell = 1 \dots L \quad (3)$$

$$\mathbf{y} = \text{LN}(\mathbf{z}_L^0) \quad (4)$$

Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable “classification token” to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).

The Transformer encoder (Vaswani et al., 2017) consists of alternating layers of multiheaded self-attention (MSA, see Appendix A) and MLP blocks (Eq. 2, 3). Layernorm (LN) is applied before every block, and residual connections after every block (Wang et al., 2019; Baevski & Auli, 2019).

Equation 2: The MSA Block

MSA = Multi-Head Self Attention

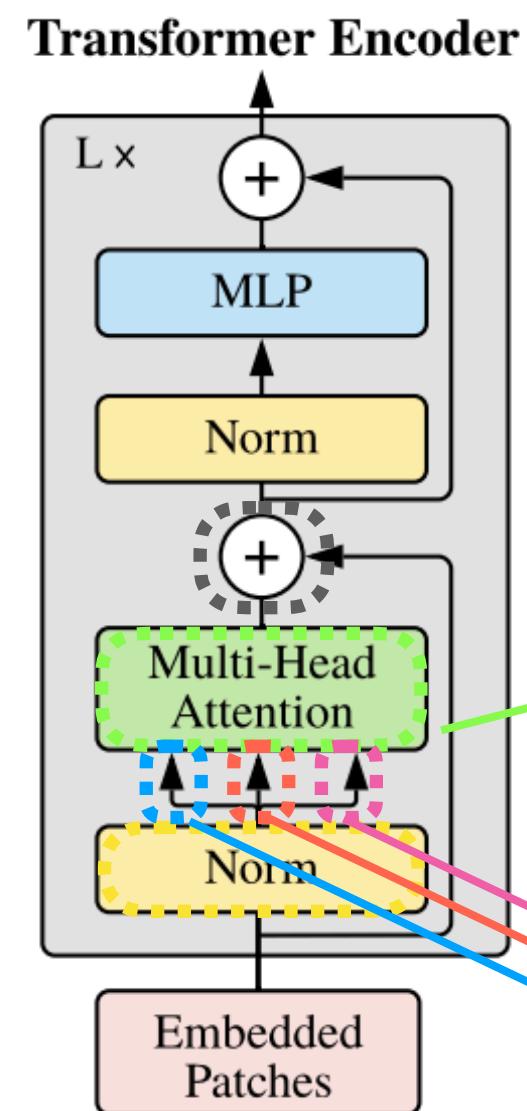
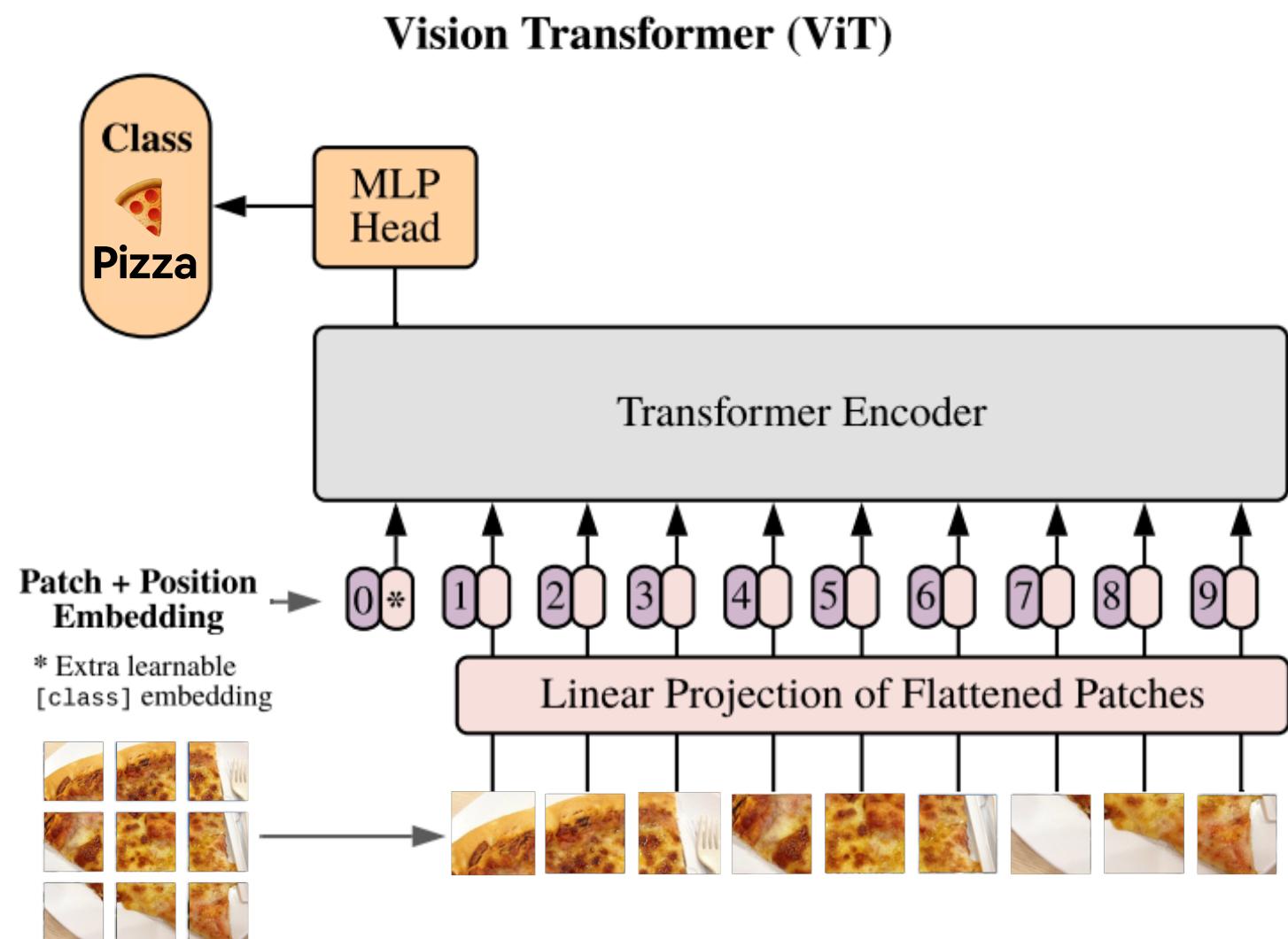


Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable “classification token” to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).

q = query
k = key
v = value

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{\text{pos}}, \quad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{\text{pos}} \in \mathbb{R}^{(N+1) \times D} \quad (1)$$

$$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \quad \ell = 1 \dots L \quad (2)$$

$$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad \ell = 1 \dots L \quad (3)$$

$$\mathbf{y} = \text{LN}(\mathbf{z}_L^0) \quad (4)$$

The Transformer encoder (Vaswani et al., 2017) consists of alternating layers of multiheaded self-attention (MSA, see Appendix A) and MLP blocks (Eq. 2, 3). Layernorm (LN) is applied before every block, and residual connections after every block (Wang et al., 2019; Baevski & Auli, 2019).

A MULTIHEAD SELF-ATTENTION From “Attention is all you need” paper

Standard qkv self-attention (SA, Vaswani et al. (2017)) is a popular building block for neural architectures. For each element in an input sequence $\mathbf{z} \in \mathbb{R}^{N \times D}$, we compute a weighted sum over all values \mathbf{v} in the sequence. The attention weights A_{ij} are based on the pairwise similarity between two elements of the sequence and their respective query \mathbf{q}^i and key \mathbf{k}^j representations.

$$[\mathbf{q}, \mathbf{k}, \mathbf{v}] = \mathbf{z} \mathbf{U}_{qkv} \quad \mathbf{U}_{qkv} \in \mathbb{R}^{D \times 3D_h}, \quad (5)$$

$$A = \text{softmax} \left(\mathbf{q} \mathbf{k}^\top / \sqrt{D_h} \right) \quad A \in \mathbb{R}^{N \times N}, \quad (6)$$

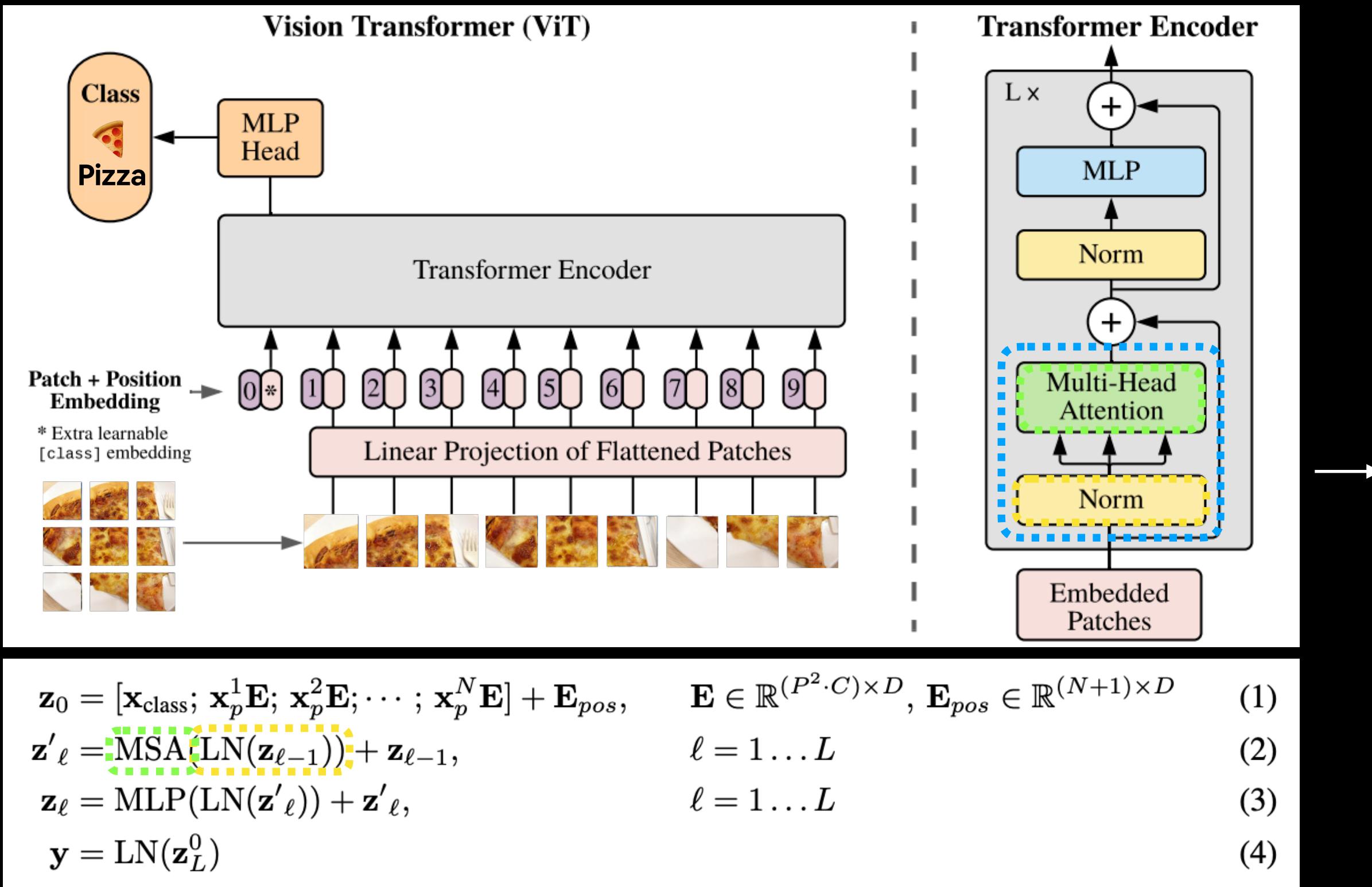
$$\text{SA}(\mathbf{z}) = A \mathbf{v}. \quad (7)$$

Multihead self-attention (MSA) is an extension of SA in which we run k self-attention operations, called “heads”, in parallel, and project their concatenated outputs. To keep compute and number of parameters constant when changing k , D_h (Eq. 5) is typically set to D/k .

$$\text{MSA}(\mathbf{z}) = [\text{SA}_1(\mathbf{z}); \text{SA}_2(\mathbf{z}); \dots; \text{SA}_k(\mathbf{z})] \mathbf{U}_{msa} \quad \mathbf{U}_{msa} \in \mathbb{R}^{k \cdot D_h \times D} \quad (8)$$

Equation 2: The MSA Block

MSA = Multi-Head Self Attention



```
from torch import nn

# 1. Create a class that inherits from nn.Module
class MultiheadSelfAttentionBlock(nn.Module):
    """Creates a multi-head self-attention block ("MSA block" for short).
    """

# 2. Initialize the class with hyperparameters from Table 1
def __init__(self,
            embedding_dim:int=768, # Hidden size D from Table 1 for ViT-Base
            num_heads:int=12, # Heads from Table 1 for ViT-Base
            attn_dropout:int=0): # doesn't look like the paper uses any dropout in MSABlocks
    super().__init__()

    # 3. Create the Norm layer (LN)
    self.layer_norm = nn.LayerNorm(normalized_shape=embedding_dim)

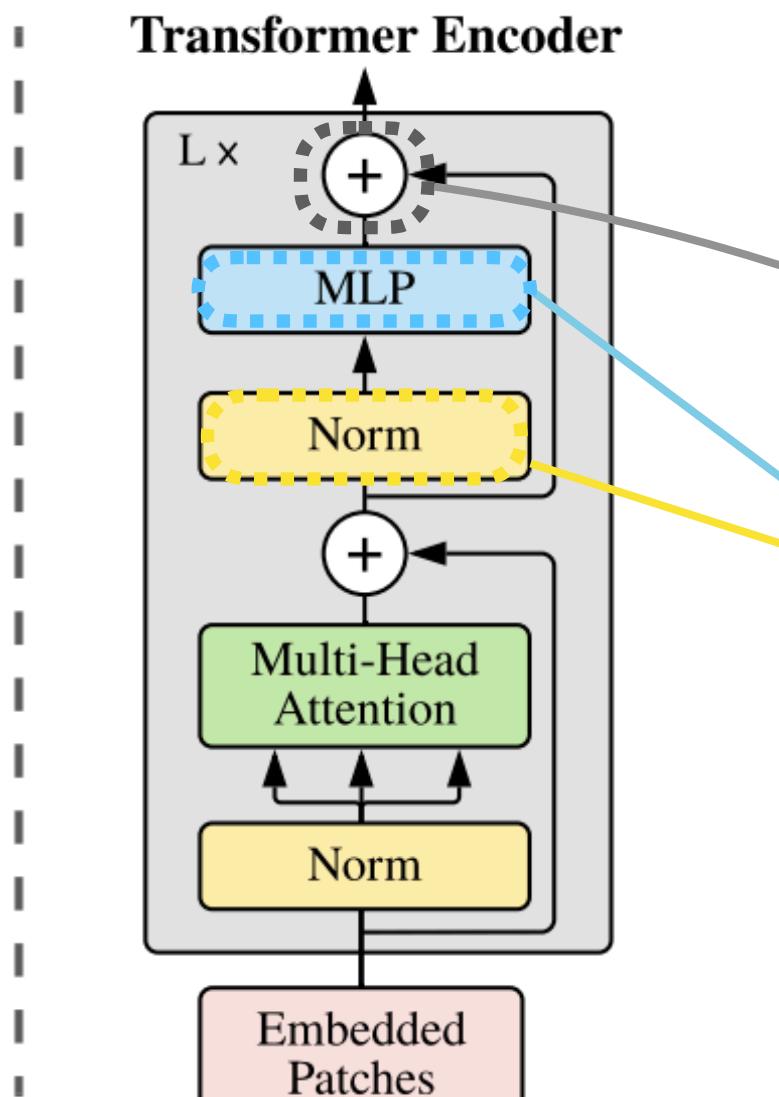
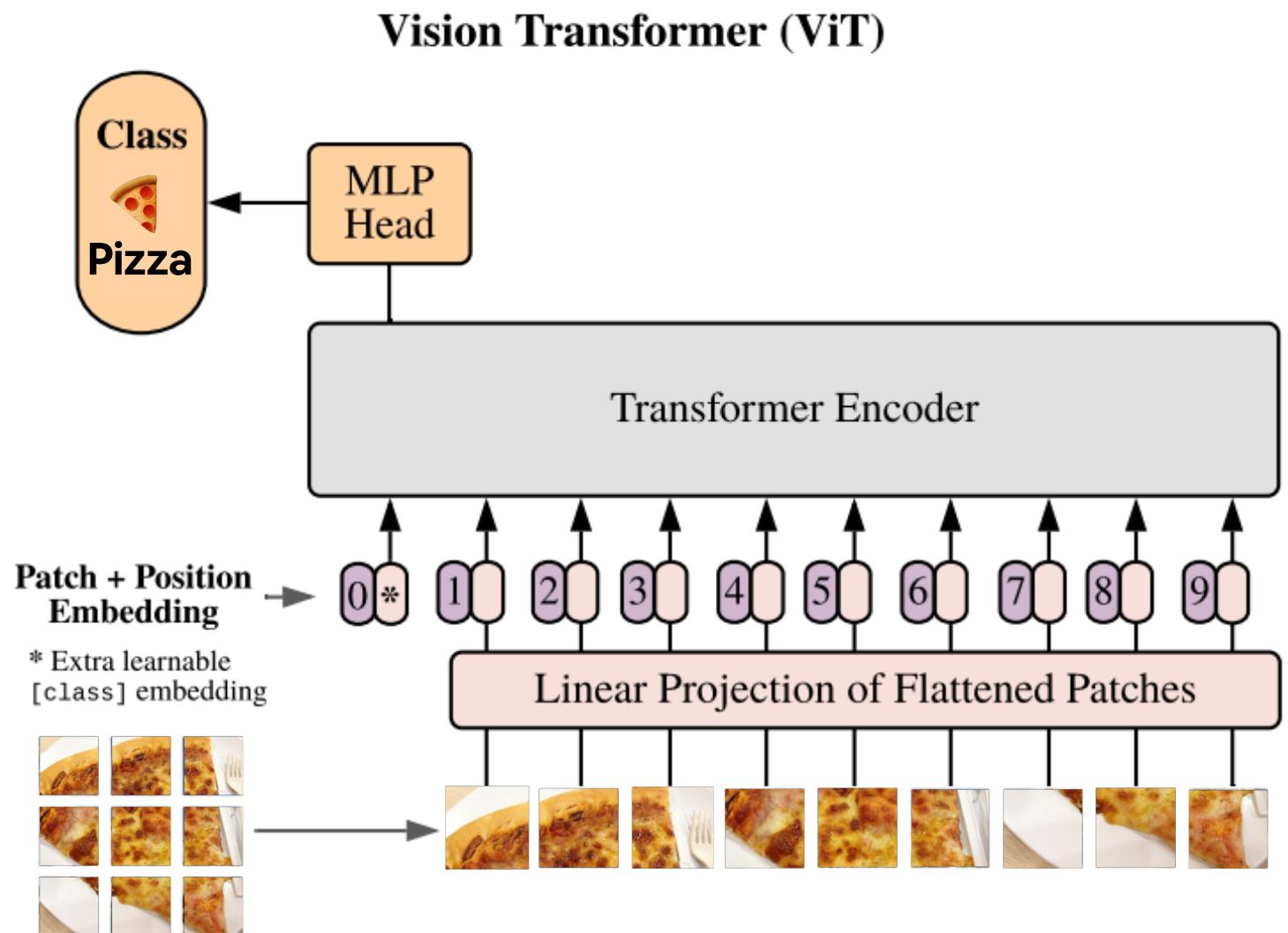
    # 4. Create the Multi-Head Attention (MSA) layer
    self.multihead_attn = nn.MultiheadAttention(embed_dim=embedding_dim,
                                                num_heads=num_heads,
                                                dropout=attn_dropout,
                                                batch_first=True) # batch dimension first?

# 5. Create a forward() method to pass the data through the layers
def forward(self, x):
    x = self.layer_norm(x)
    attn_output, _ = self.multihead_attn(query=x, # query embeddings
                                         key=x, # key embeddings
                                         value=x, # value embeddings
                                         need_weights=False) # only get layer outputs

    return attn_output
```

Equation 3: The MLP Block

MLP = Multilayer Perceptron



Equation 3 = "MLP block"

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{\text{pos}}, \quad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{\text{pos}} \in \mathbb{R}^{(N+1) \times D} \quad (1)$$

$$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \quad \ell = 1 \dots L \quad (2)$$

$$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad \ell = 1 \dots L \quad (3)$$

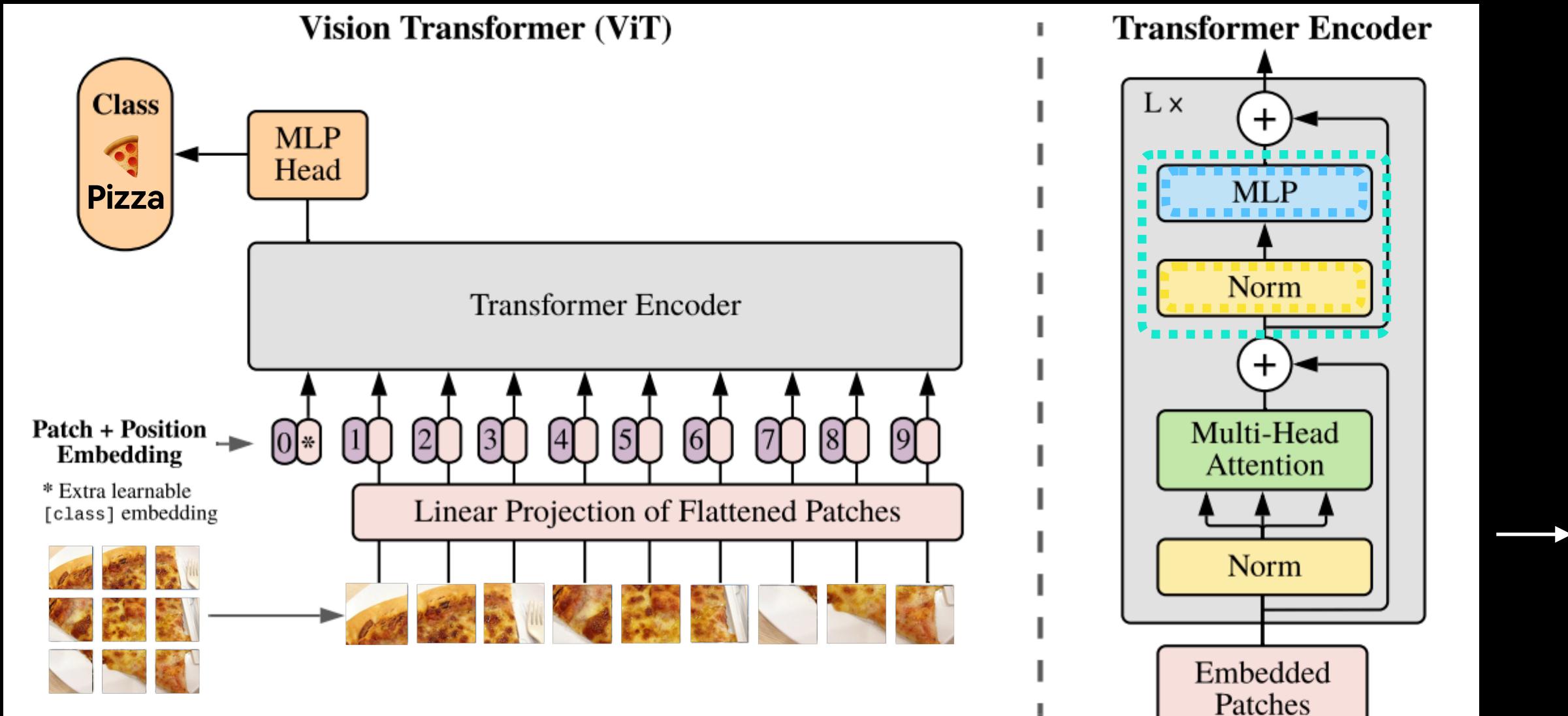
$$\mathbf{y} = \text{LN}(\mathbf{z}_L^0) \quad (4)$$

Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable “classification token” to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).

The Transformer encoder (Vaswani et al., 2017) consists of alternating layers of multiheaded self-attention (MSA, see Appendix A) and MLP blocks (Eq. 2, 3). Layernorm (LN) is applied before every block, and residual connections after every block (Wang et al., 2019; Baevski & Auli, 2019).

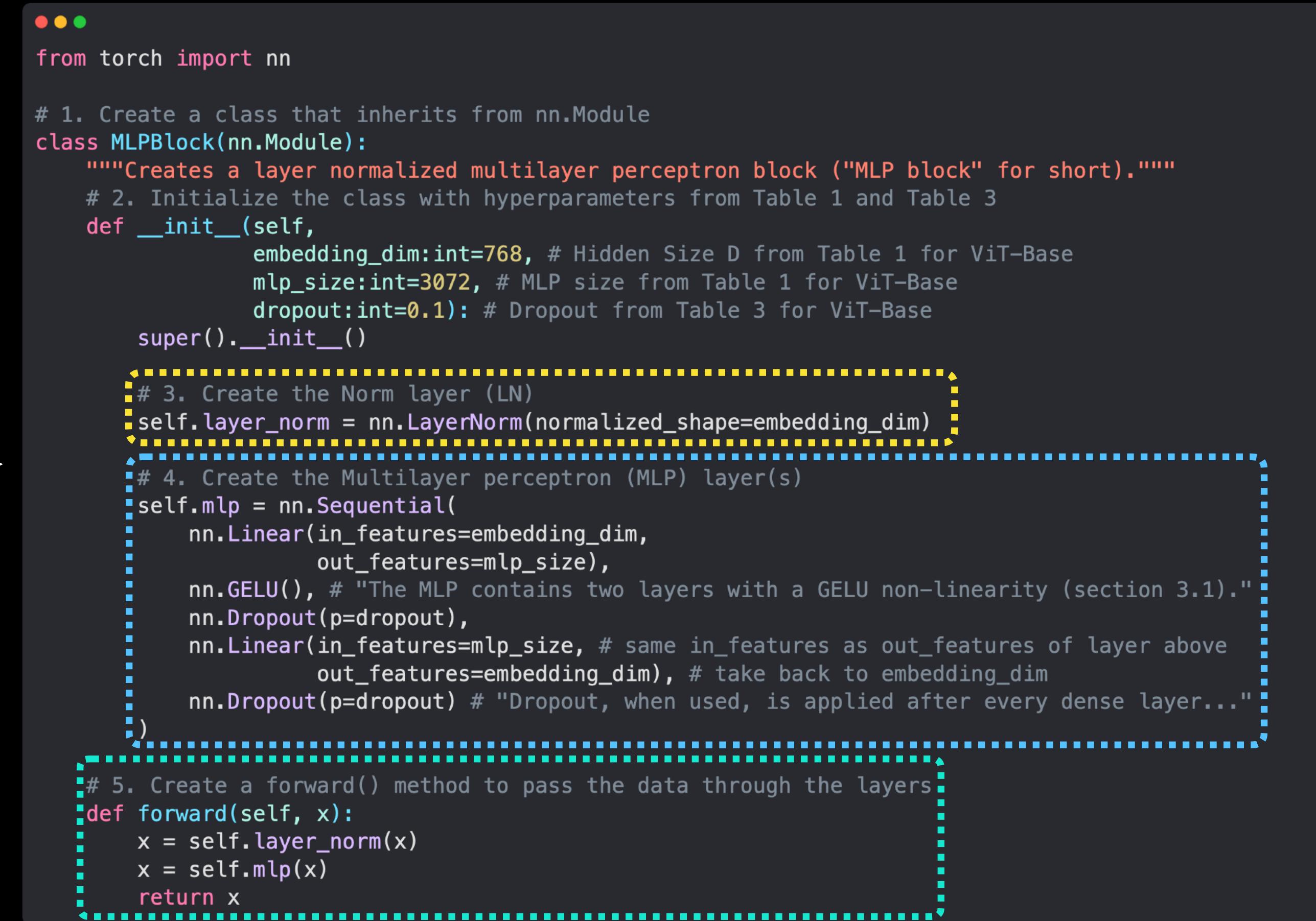
Equation 3: The MLP Block

MLP = Multilayer perceptron

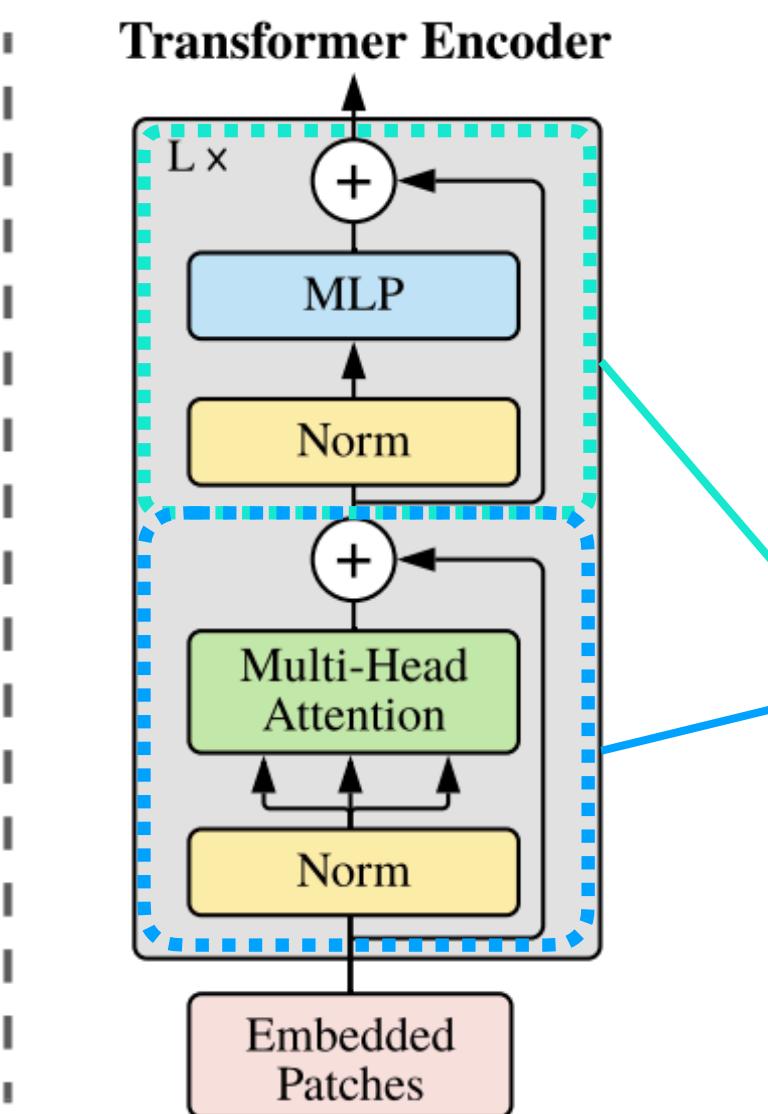
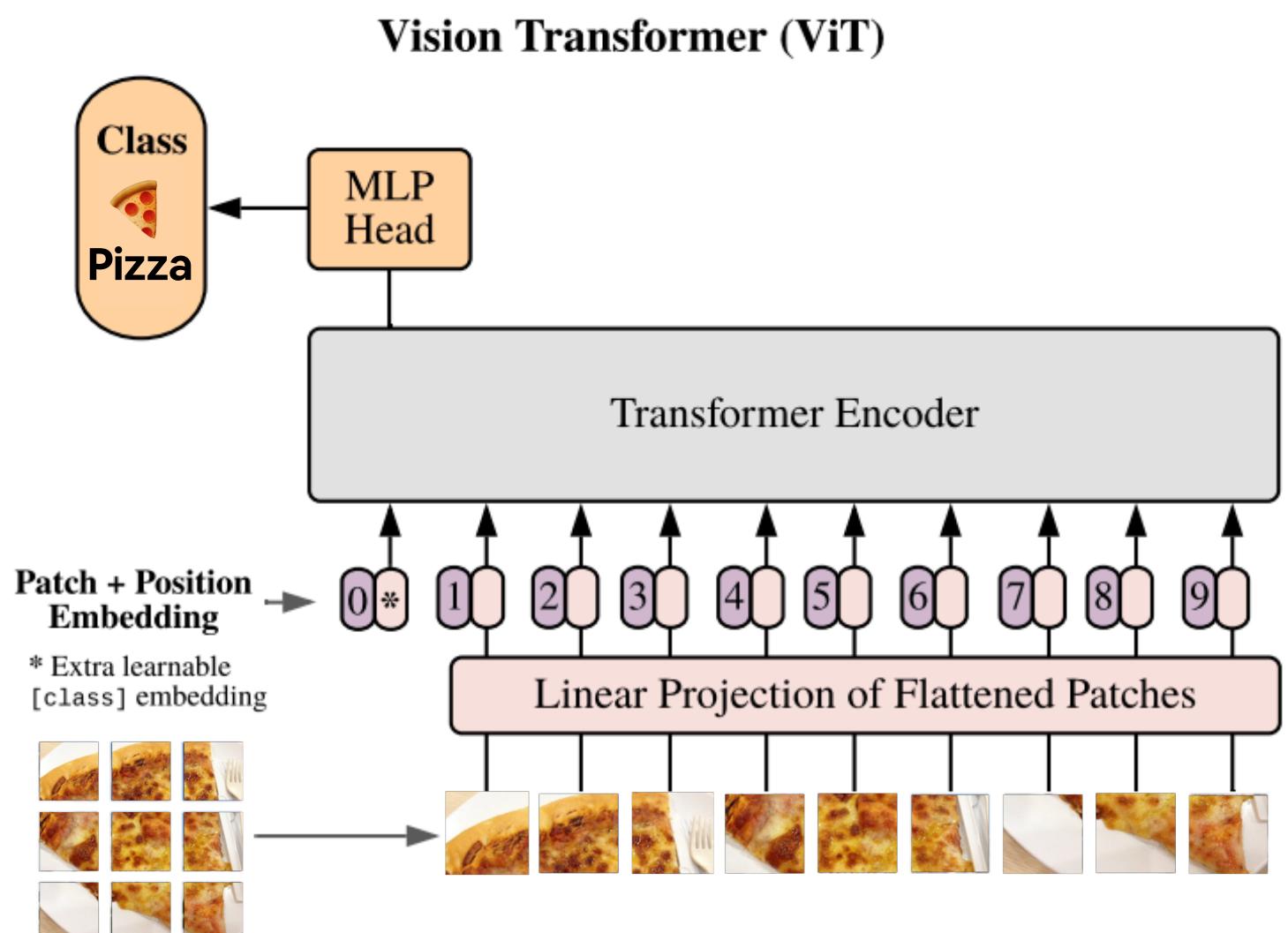


$$\begin{aligned} \mathbf{z}_0 &= [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{pos}, & \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{pos} \in \mathbb{R}^{(N+1) \times D} \\ \mathbf{z}'_\ell &= \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, & \ell = 1 \dots L \\ \mathbf{z}_\ell &= \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, & \ell = 1 \dots L \\ \mathbf{y} &= \text{LN}(\mathbf{z}_L^0) \end{aligned}$$

(1) (2) (3) (4)



The Transformer Encoder



Transformer Encoder = Alternating layers of equation 2 and 3

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}}; \mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{\text{pos}}, \quad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{\text{pos}} \in \mathbb{R}^{(N+1) \times D} \quad (1)$$

$$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_{\ell-1})) + \mathbf{z}_{\ell-1}, \quad \ell = 1 \dots L \quad (2)$$

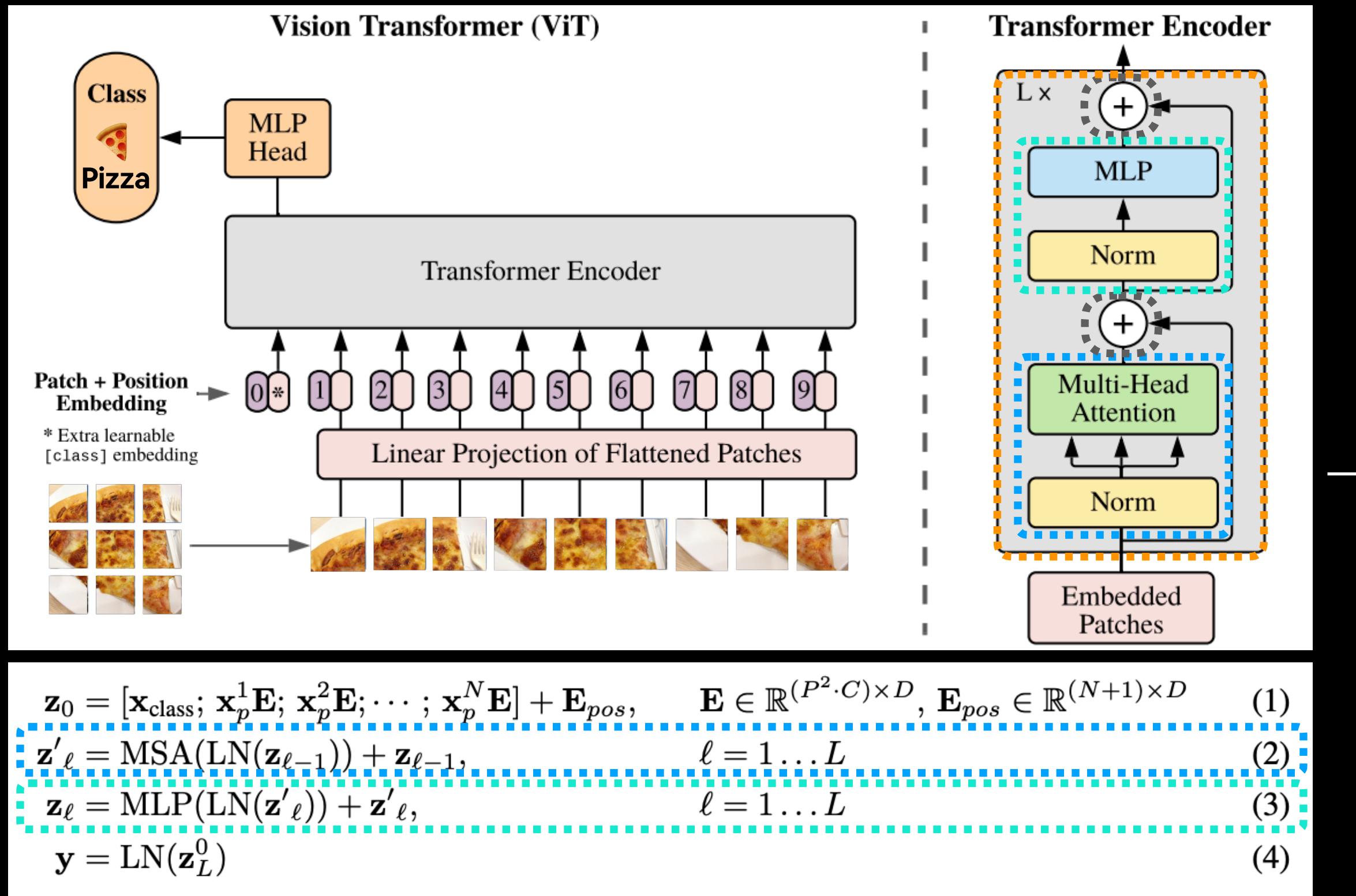
$$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad \ell = 1 \dots L \quad (3)$$

$$\mathbf{y} = \text{LN}(\mathbf{z}_L^0) \quad (4)$$

Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable “classification token” to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).

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The Transformer Encoder



```

from torch import nn

# 1. Create a class that inherits from nn.Module
class TransformerEncoderBlock(nn.Module):
    """Creates a Transformer Encoder block."""
    # 2. Initialize the class with hyperparameters from Table 1 and Table 3
    def __init__(self,
                 embedding_dim:int=768, # Hidden size D from Table 1 for ViT-Base
                 num_heads:int=12, # Heads from Table 1 for ViT-Base
                 mlp_size:int=3072, # MLP size from Table 1 for ViT-Base
                 mlp_dropout:int=0.1, # Dropout for dense layers from Table 3 for ViT-Base
                 attn_dropout:int=0): # Dropout for attention layers
        super().__init__()

        # 3. Create MSA block (equation 2)
        self.msa_block = MultiheadSelfAttentionBlock(embedding_dim=embedding_dim,
                                                      num_heads=num_heads,
                                                      attn_dropout=attn_dropout)

        # 4. Create MLP block (equation 3)
        self.mlp_block = MLPBlock(embedding_dim=embedding_dim,
                                 mlp_size=mlp_size,
                                 dropout=mlp_dropout)

    # 5. Create a forward() method
    def forward(self, x):

        # 6. Create residual connection for MSA block (add the input to the output)
        x = self.msa_block(x) + x

        # 7. Create residual connection for MLP block (add the input to the output)
        x = self.mlp_block(x) + x

    return x

```