Brain Tumor Detection with Vision Transformers

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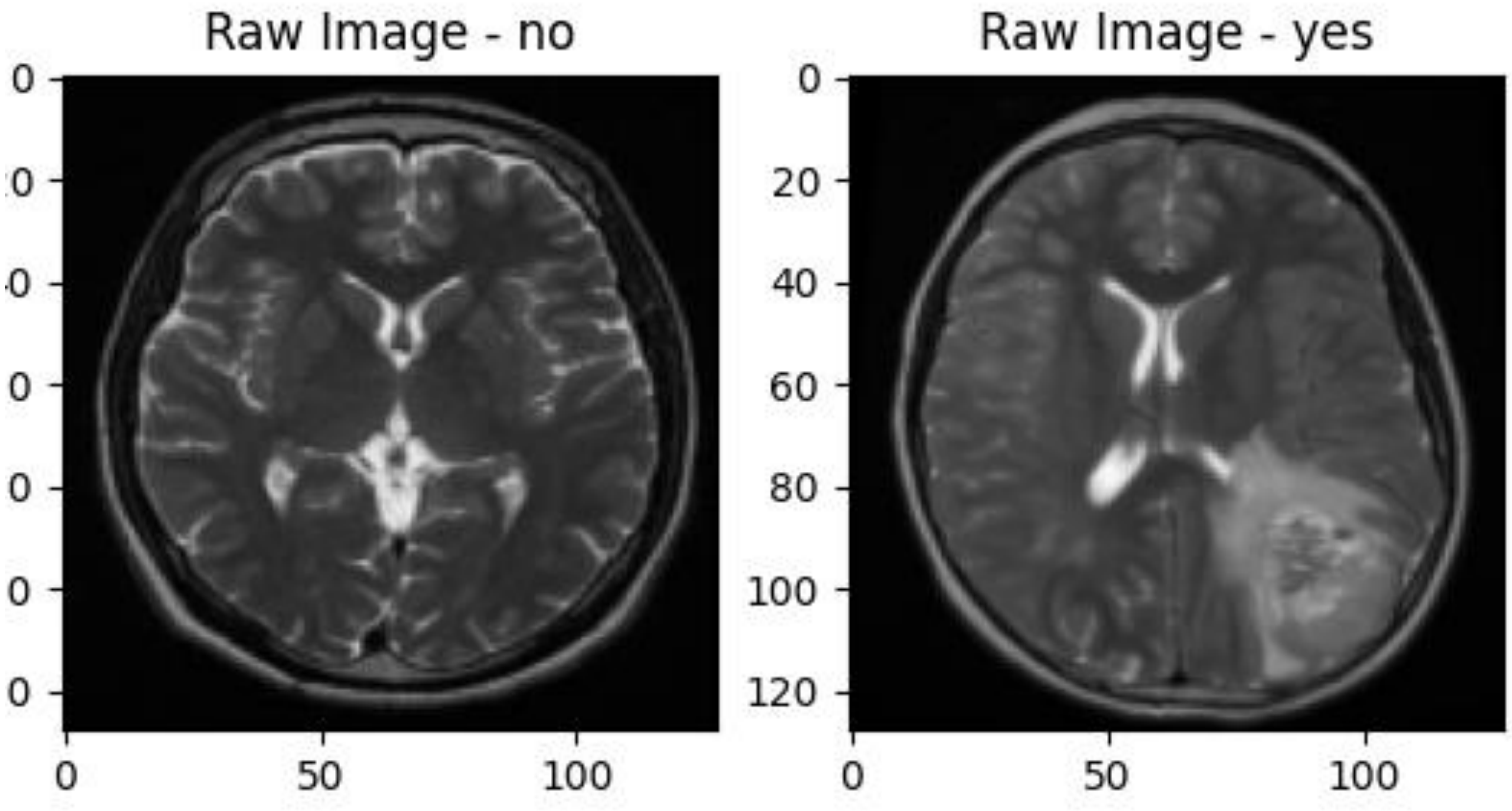
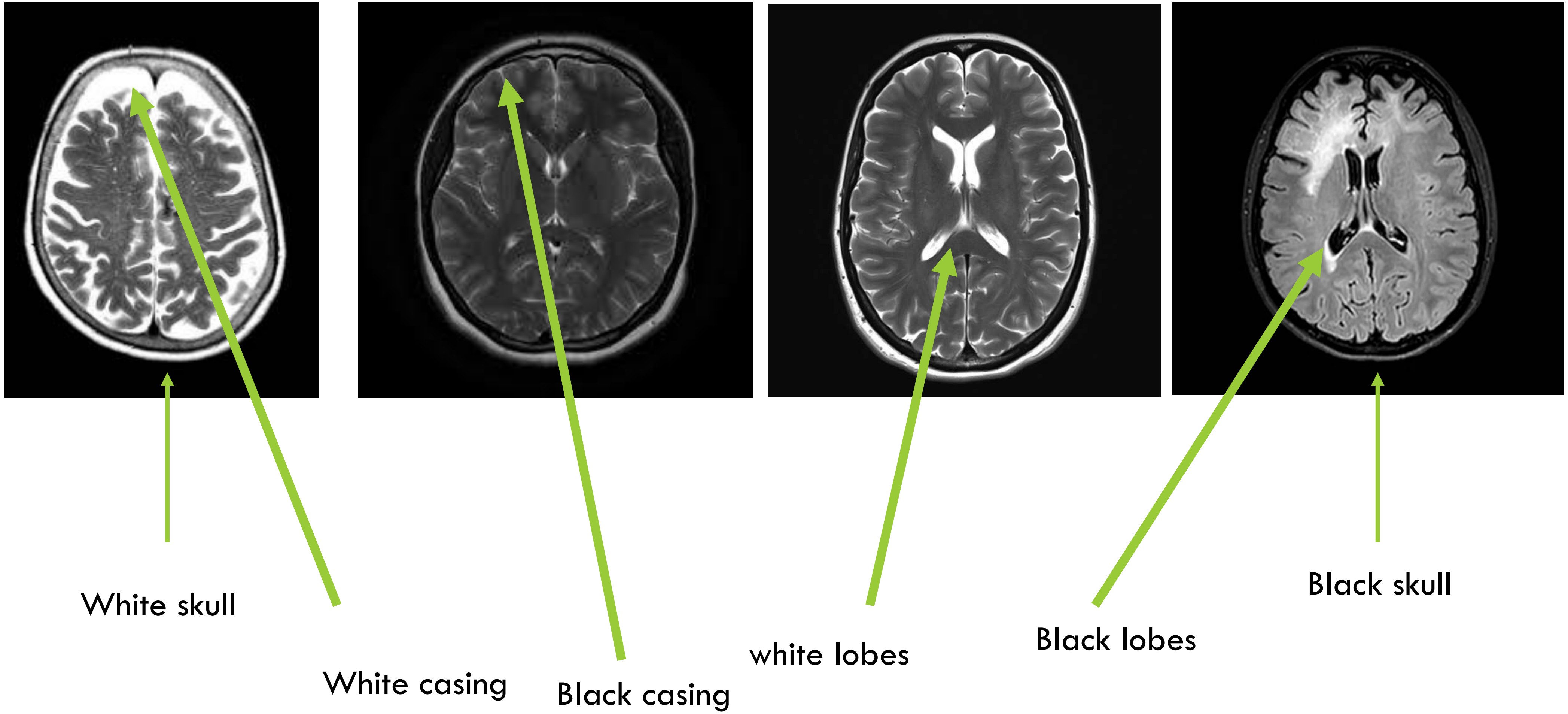
BRAIN TUMOR DETECTION KAGGLE CHALLENGE

Dataset contain 253 MRI images categorized as yes/no brain tumor detection diagnosed



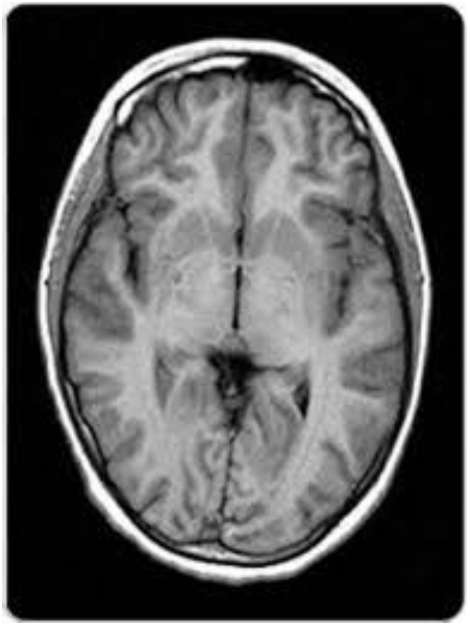
REVIEW DATASET CHALLENGES

- Inconsistent grayscale
- Casing , lobes and skull sometimes black sometimes white

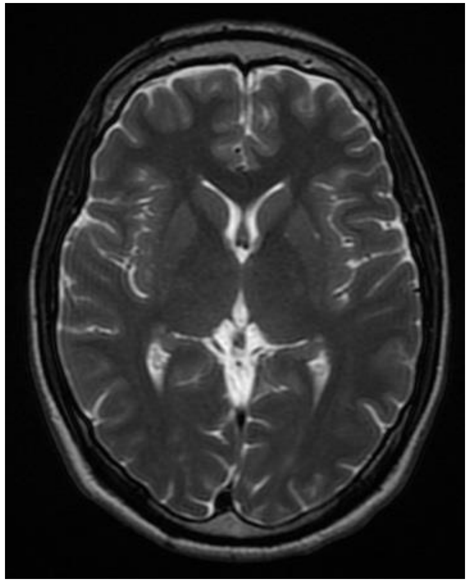


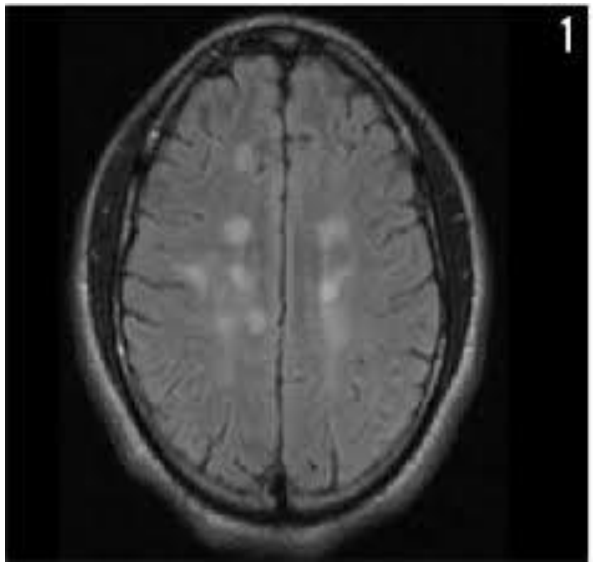
REVIEW DATASET CHALLENGES

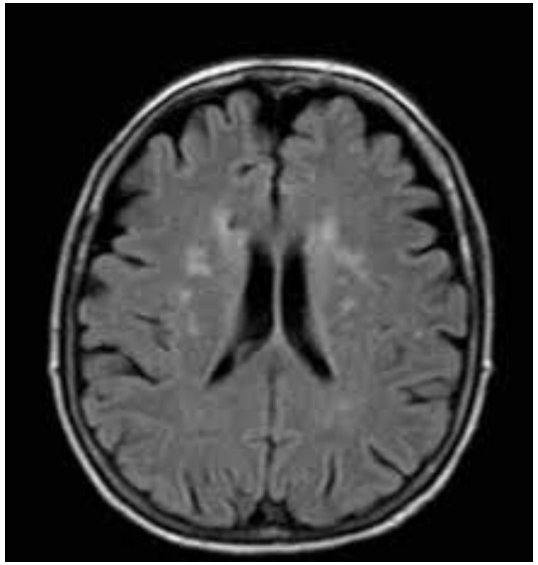
- Central lobes can be in many shapes or not be at all and might be classified as tumor



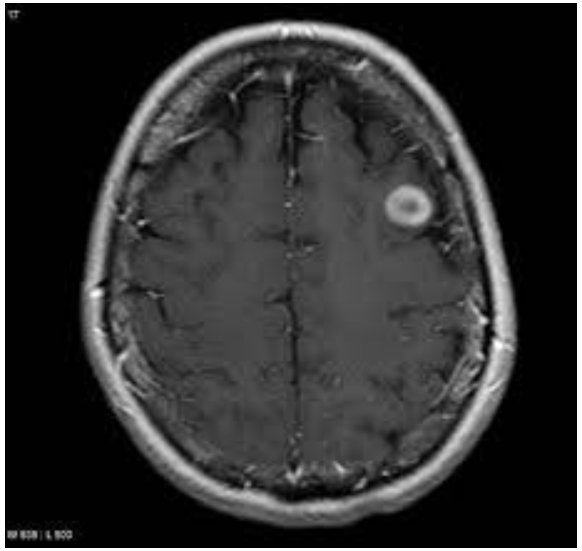
No tumor





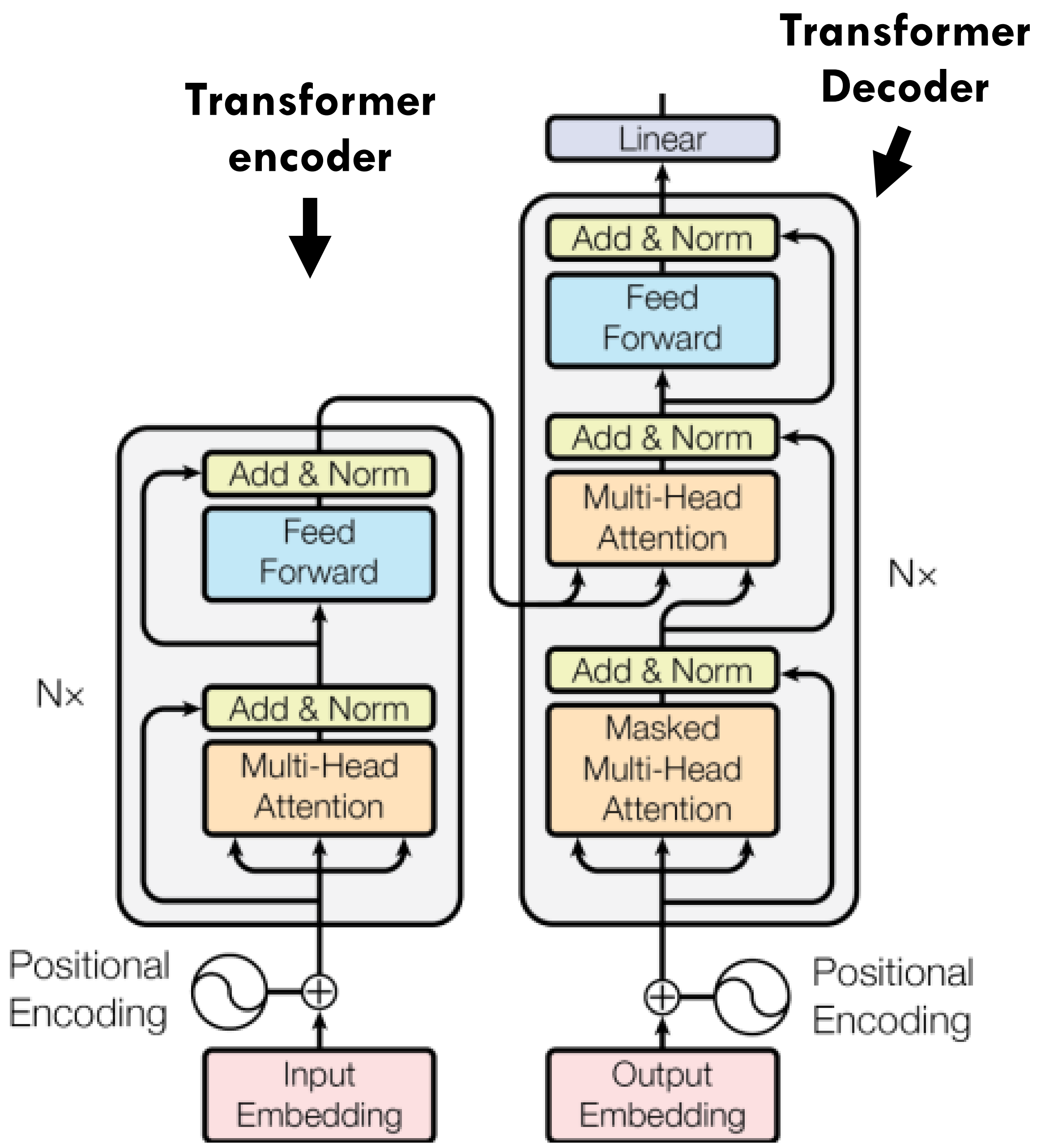


has tumor



TRANSFORMER ARCHITECTURE

In image classification the encoder is the primary component for classifications



TRANSFORMER ENCODER BLOCK

Transformer encoder block is composed of 5 primary components :

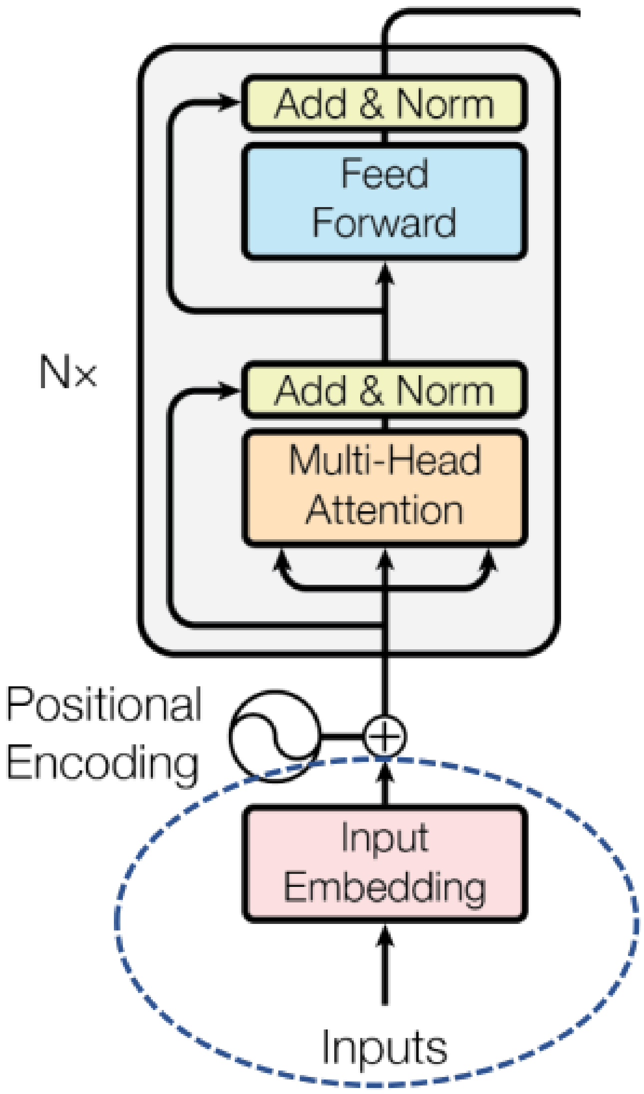
1. Input embedding

2. Positional encoding

3. Multi Head Attention

4.Feed Forward Network

5. output layer



INPUT EMBEDDING LAYER

<u>Input Embedding in NLP</u>

Input emending block is basically a neural network that is designated to **project** each

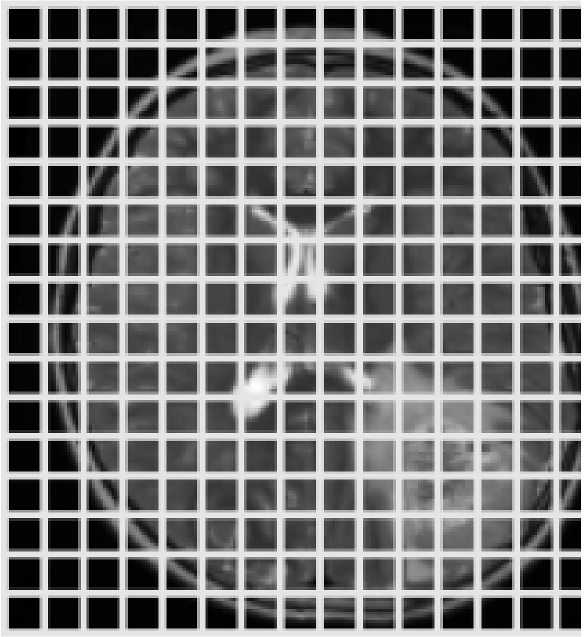
Of the input sequences into a dense numerical representation that the transformer model can process.

For example :

Each word may get 256 vector (d_module) representation

Whereas “child” – “girl” is equivalent or close to “king”- “queen”

Images as input sequences of patches



STEP 1 - IMAGE PATCHING DIVISION

INPUT EMBEDDING IN IMAGES

In visions transformers we split the original image into patches ,

And each patch Is projected into vector.

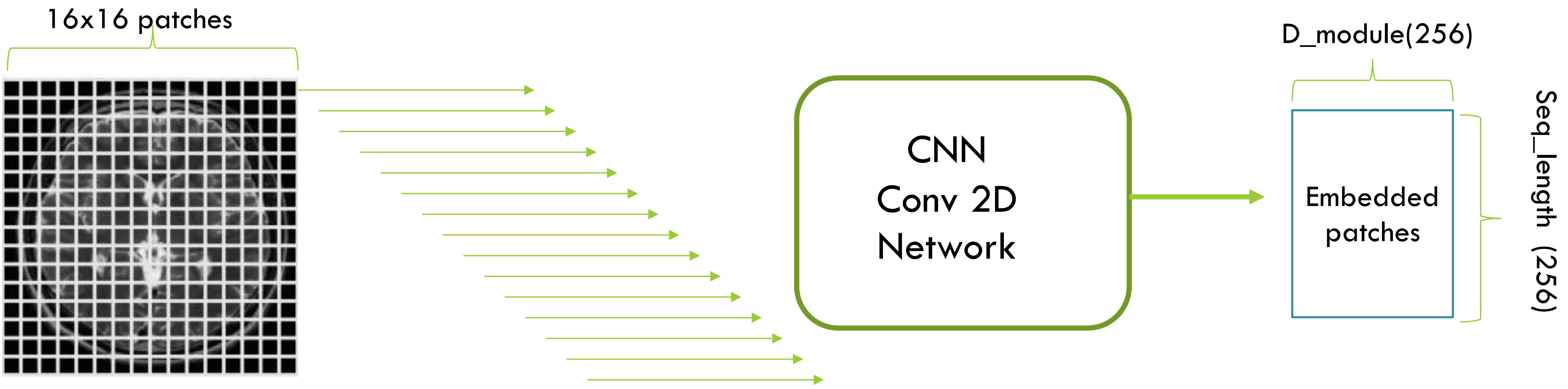
the input embedding more likely to be implemented by CNN rather than fully connected networks.

Each of the image patches is projected through conv 2D network

Where the Output of the 2D Conv network is the patches embedded values

STEP 2 INPUT EMBEDDING

- Each patch from the patched image is projected into d_module(256) sized vector within CNN
- Same content are projected to same embedded vectors



Patch projection through embedding layer

POSITIONAL ENCODING

Transformer encoder block is composed of 5 primary components :

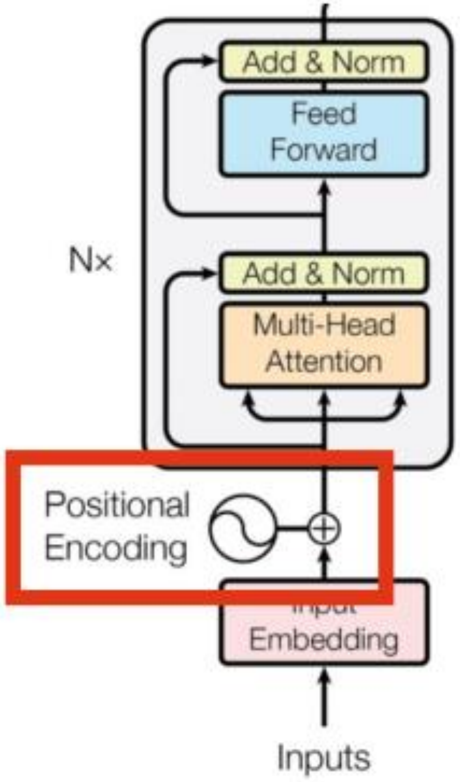
1. Input embedding

2. Positional encoding

3. Multi Head Attention

4.Feed Forward Network

5. output layer

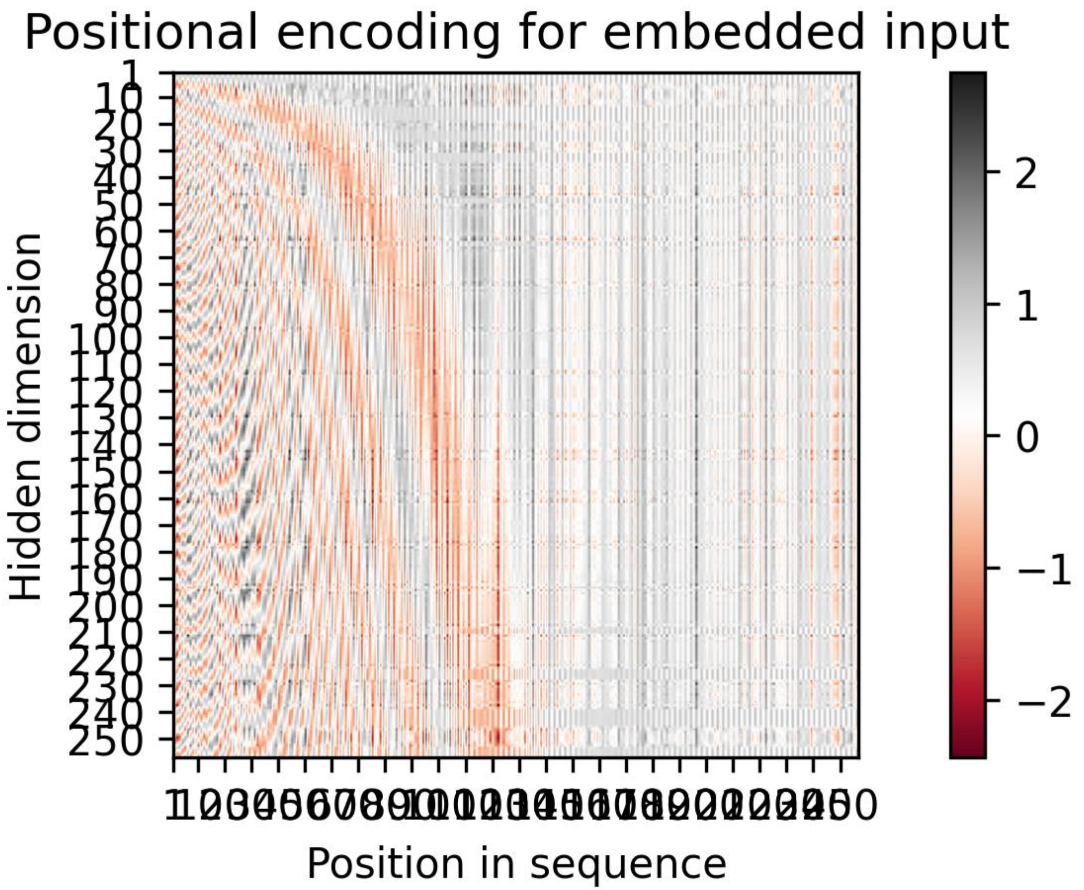


POSITIONAL ENCODING CHART FOREACH PATCH

Positional encoding adds to each patch some information regarding its position in the original image.

Helps us to **distinct “close” and “far” patches**

Helps to represent patterns that can be learned by our model



$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$

$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

MULTI HEAD ATTENTION

Transformer encoder block is composed of 5 primary components :

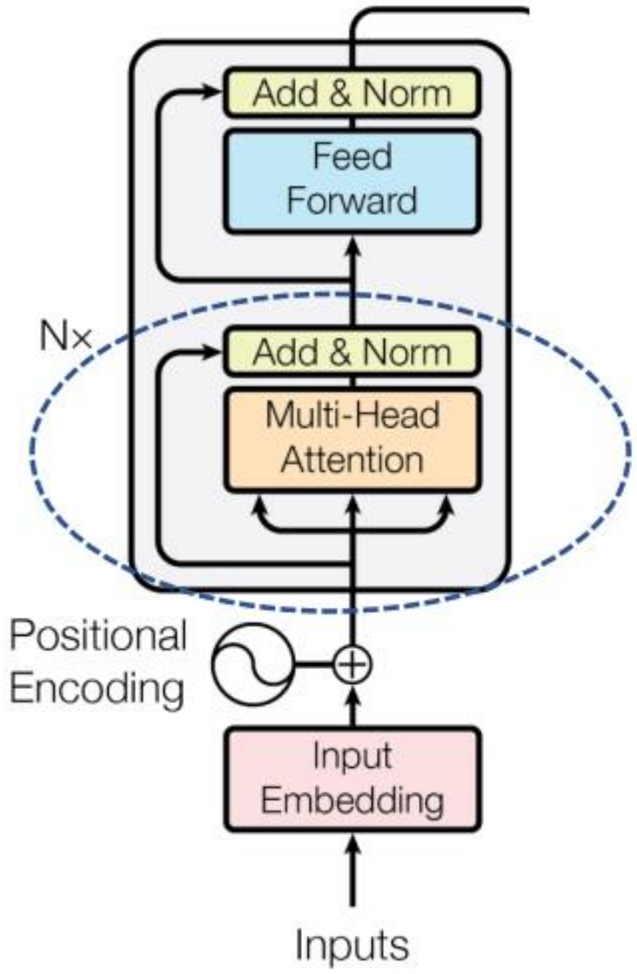
1. Input embedding

2. Positional encoding

3. Multi Head Attention

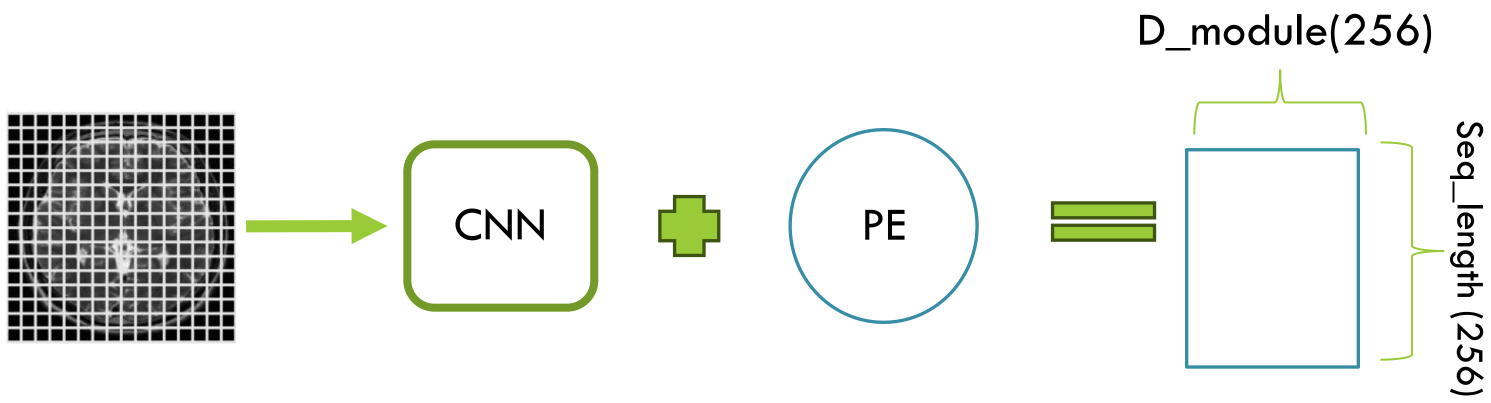
4.Feed Forward Network

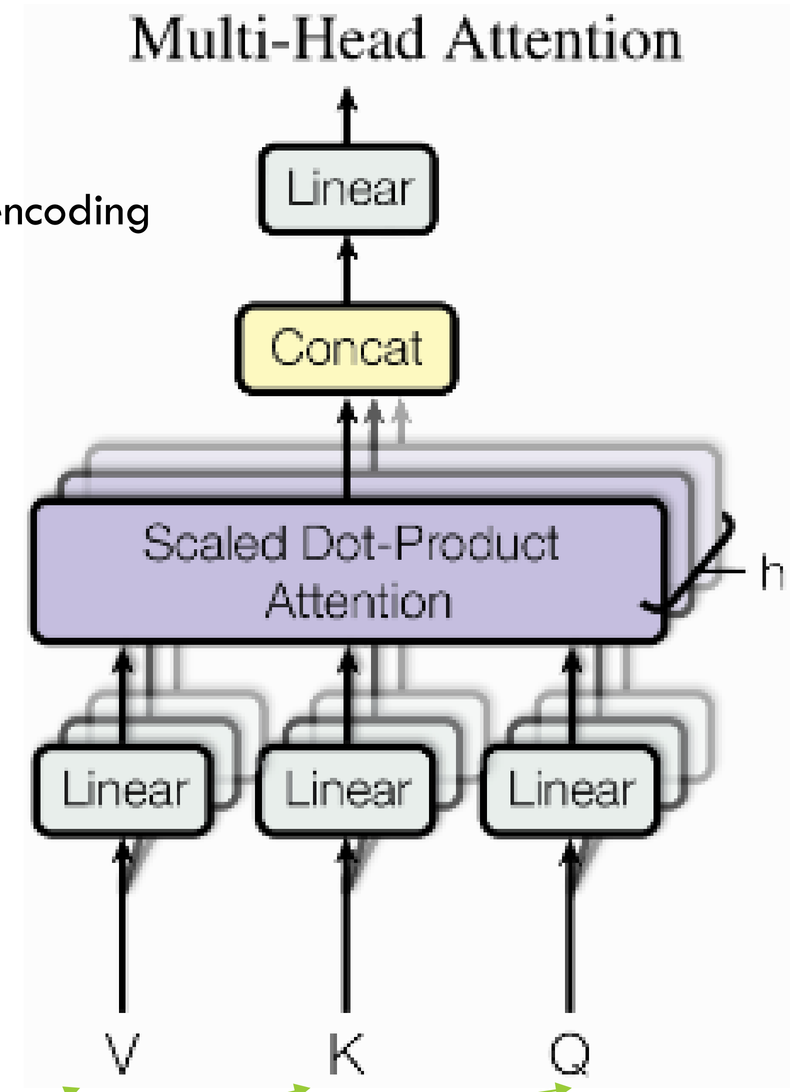
5. output layer



KEY QUERY VALUE INPUTS

- The **Input** to the MHA is patches projected thorough CNN + positional encoding



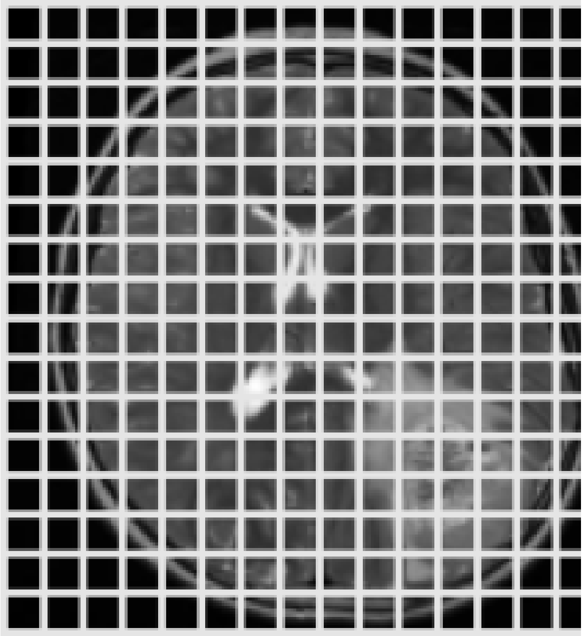


X_inp (Seq,d_module) is duplicate into :

QUESTION #1

Images as input sequences of patches

Bottom corners of image,
Denote black background ,
irrelevant for classification



Are these 2 patches ideally have the same Embedded values ?

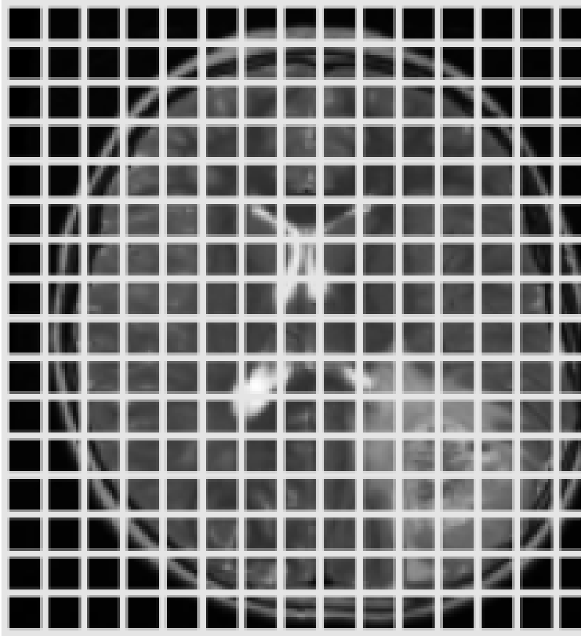
QUESTION #1

Images as input sequences of patches

Bottom corners of image,
Denote black background ,
irrelevant for classification

Ideally

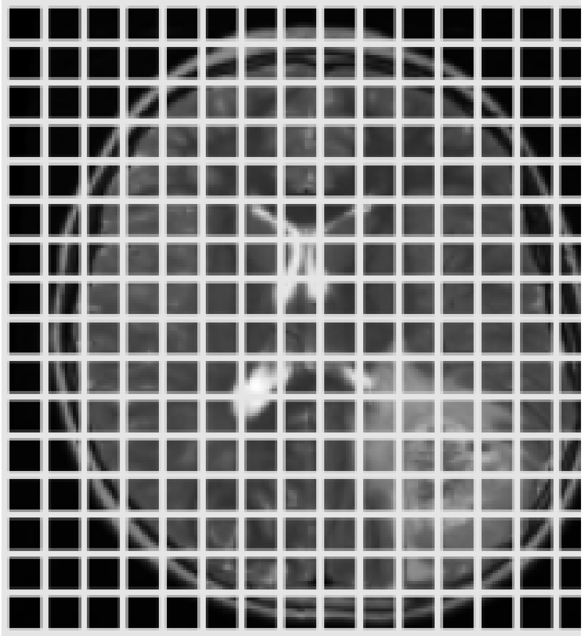
Yes !



Are these 2 patches ideally have the same Embedded values ?

QUESTION #2

Images as input sequences of patches



Bottom corners of image,
Denote black background ,
irrelevant for classification

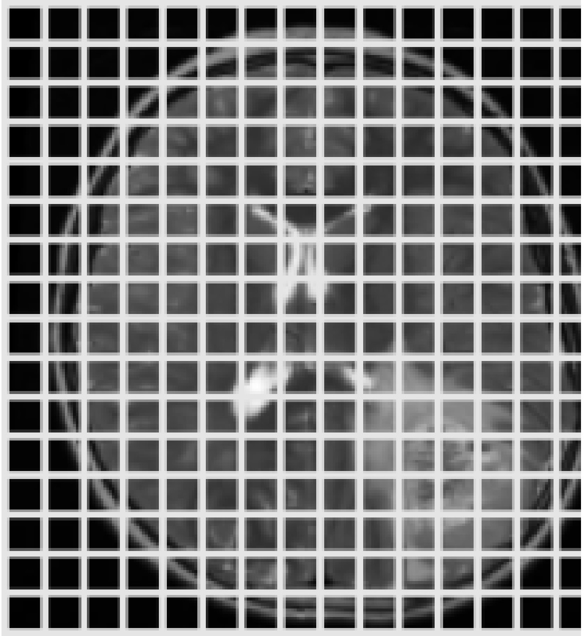
Are these 2 patches ideally have the same K Q V values ?

QUESTION #2

Images as input sequences of patches

Bottom corners of image,
Denote black background ,
irrelevant for classification

NO !
We added Positional Encoding for sequence distinction



Are these 2 patches ideally have the same K Q V values ?

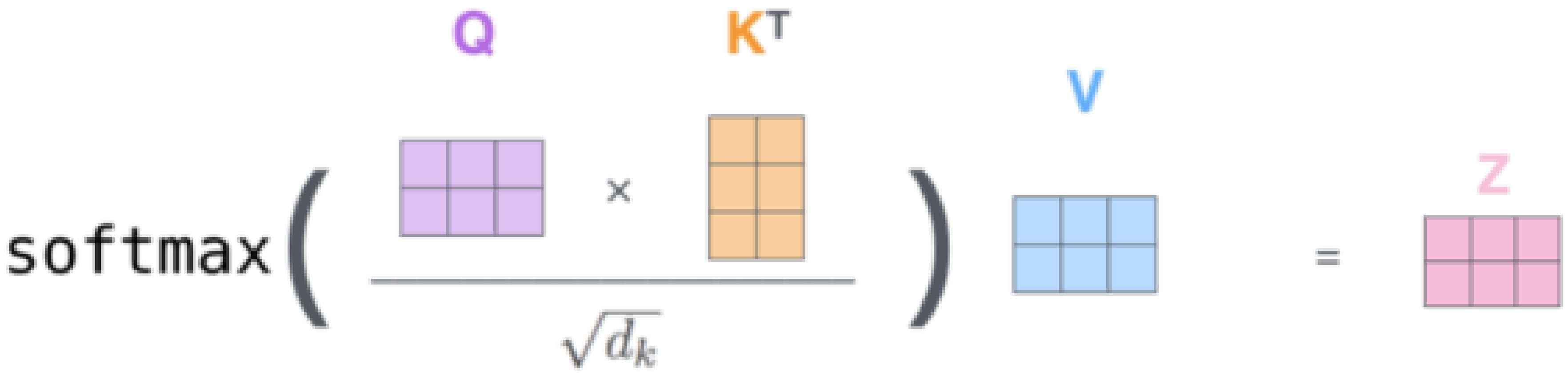
SELF HEAD ATTENTION

Patch_inp -> input_Embeding + positional encoding =>

X_inp (Seq,d_module) is duplicate into :

- Q (Seq_Len, d_module)
- K (Seq_Len, d_module)
- V (Seq_Len, d_module)

Seq x Seq Attention map

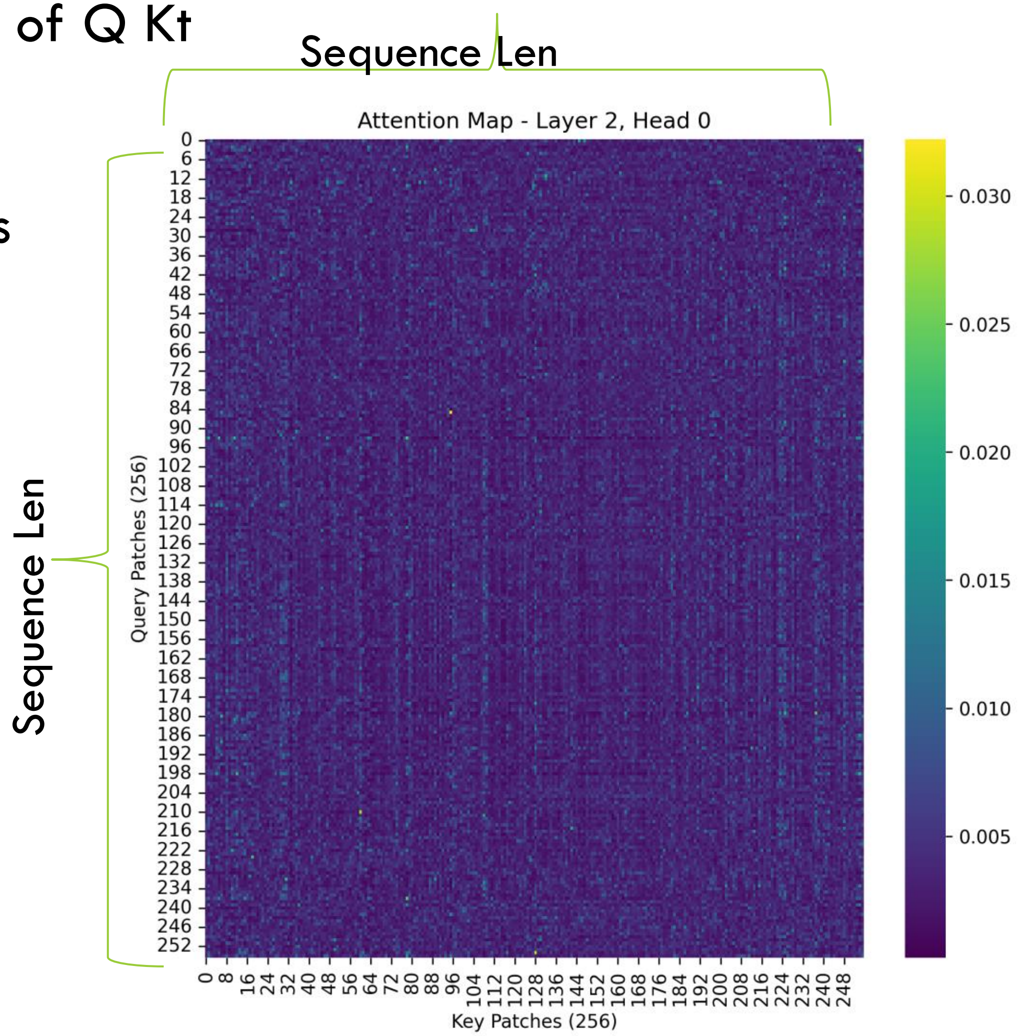


<u>Z matrix has</u>:

1. Patches embedding info
2. PE info
3. Attention Map info

ATTENTION MAP

- Attention map is an output of the Softmax activation of Q Kt
- It has [Sequence_Len X Sequence_Len] dimensions
- Each cell denote the **Attention** Aij between 2 patches
- Sum of columns provide patch importance
- Attention map assume some patches are more important then others – and emphasize them



How to compute Self-Attention?

Example from NLP area:

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

	YOUR	CAT	IS	A	LOVELY	CAT
YOUR	0.268	0.119	0.134	0.148	0.179	0.152
CAT	0.124	0.278	0.201	0.128	0.154	0.115
IS	0.147	0.132	0.262	0.097	0.218	0.145
A	0.210	0.128	0.206	0.212	0.119	0.125
LOVELY	0.146	0.158	0.152	0.143	0.227	0.174
CAT	0.195	0.114	0.203	0.103	0.157	0.229

(6, 6)

X

V

(6, 512)

=

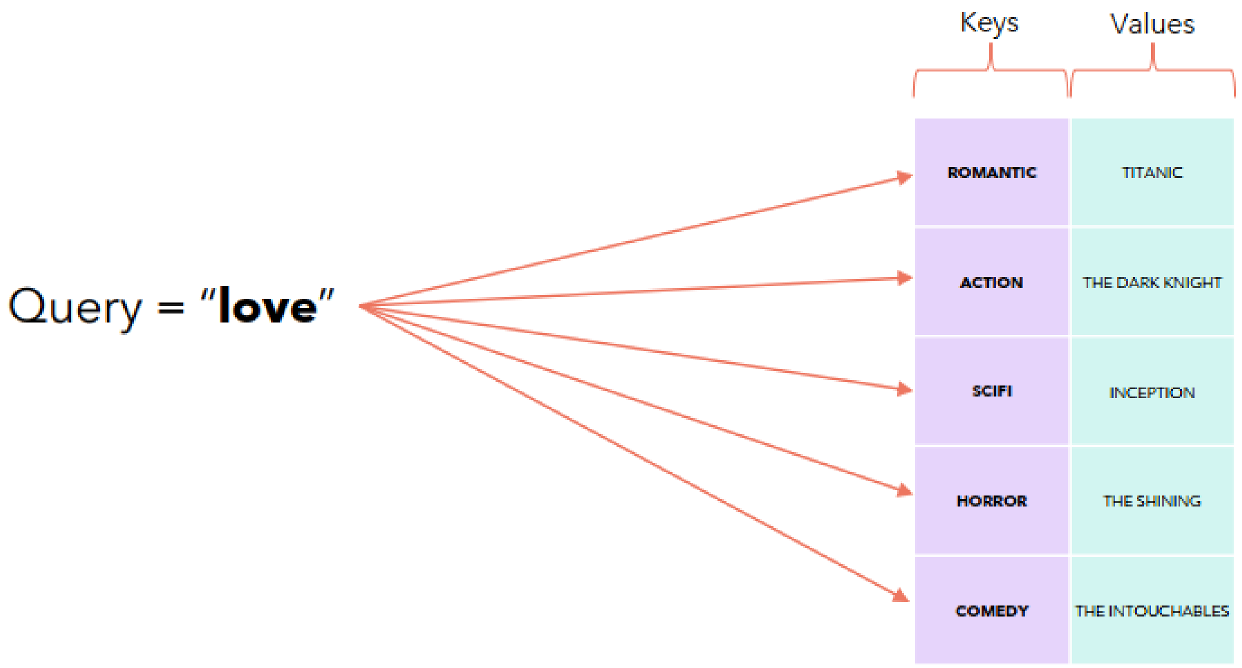
Attention

(6, 512)

Each row in this matrix captures not only the meaning (given by the embedding) or the position in the sentence (represented by the positional encodings) but also each word's interaction with other words.

Q , K , V VALUES

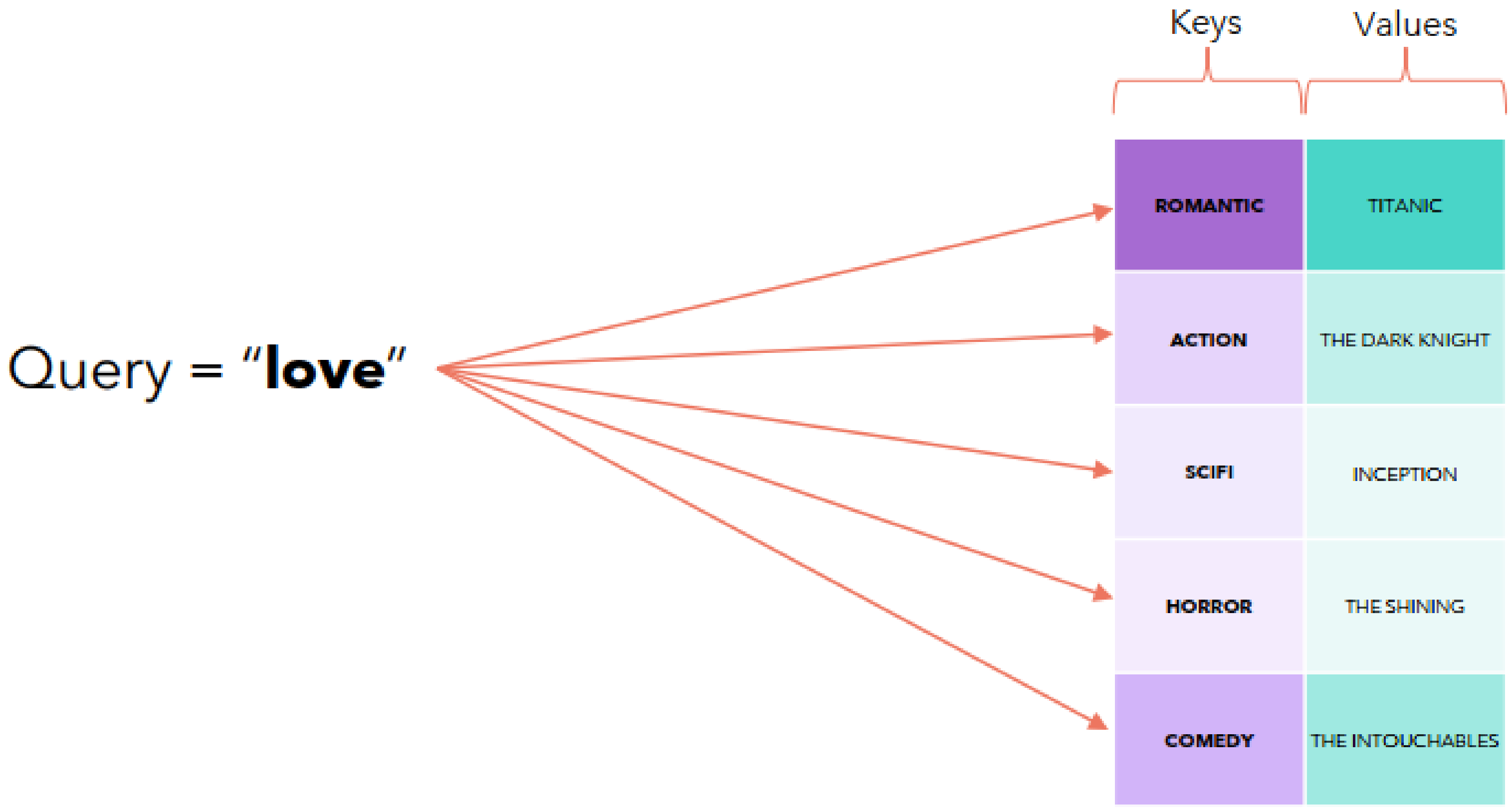
Suppose you are challenging GPT for movie recommendation within the word ‘love’



* this could be a Python dictionary or a database table.

Q , K , V VALUES

Attention mechanism shall mark up the highest probability values based on the attention map

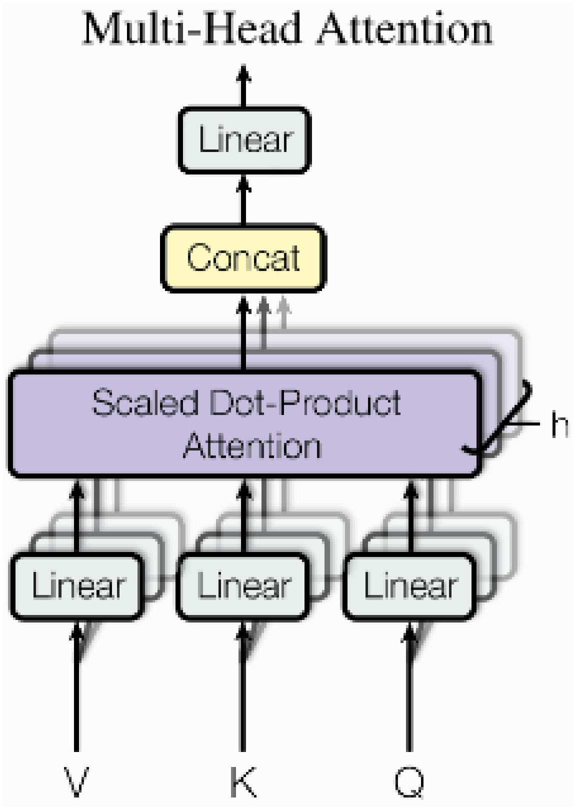


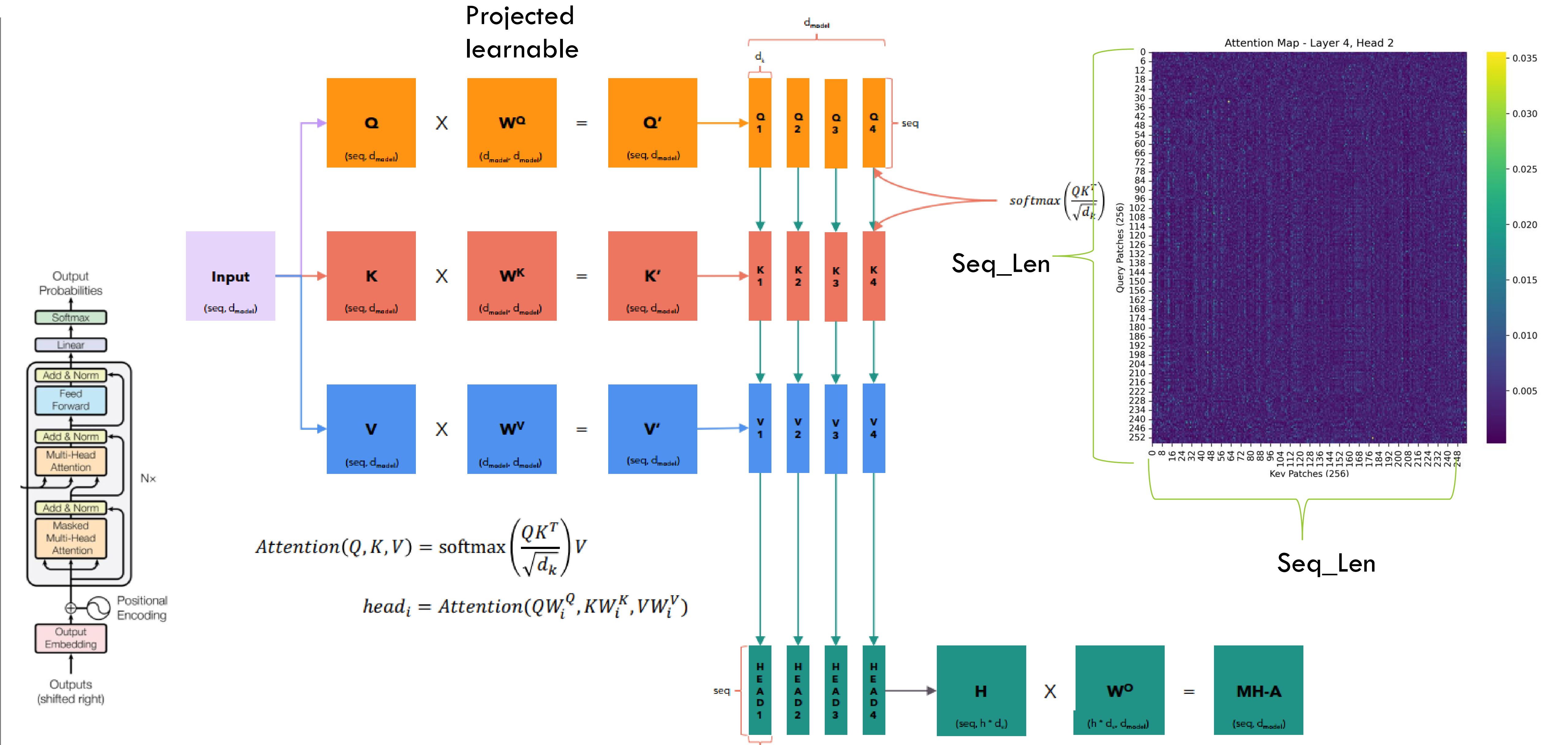
MULTI HEAD ATTENTION

Is self head attention **duplicated N times:**

- Input data include
  - Embedding foe each patch / word
  - Positional encoding

- Each head process same data within different **perspective**
  - Subject – object
  - Cause and effect
  - Verb – noun





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

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$

$$MultiHead(Q,K,V) = Concat(head_1 \ \dots head_h)W^O$$

seq = sequence length

d_{model} = size of the embedding vector

h = number of heads

TRAINING NETWORK…

Based on 253 images :

train_loss= 0.00429
train_acc=1.000
val_loss= 1.910
val_acc=0.692

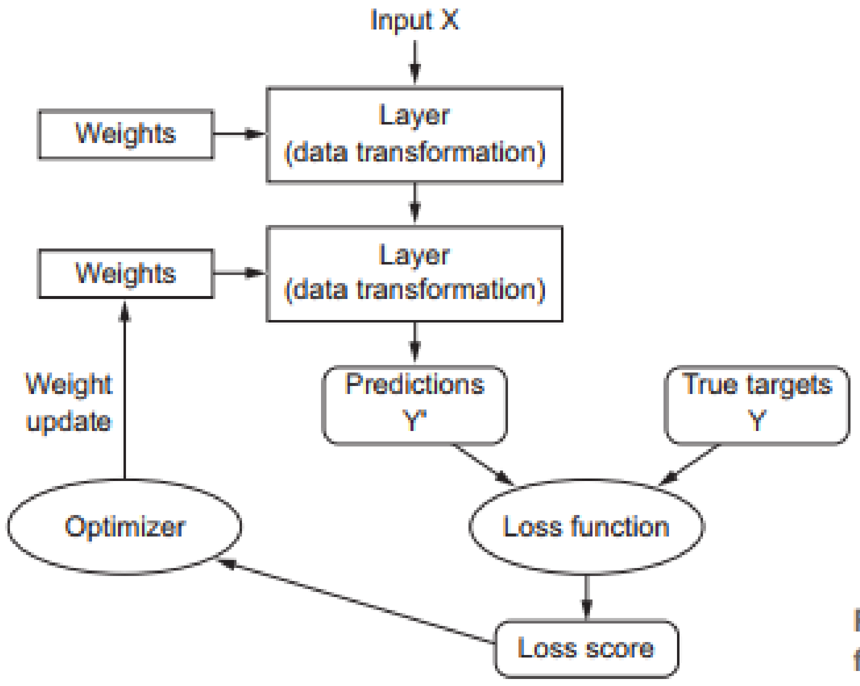


Figure 1.9 The loss score is used as a feedback signal to adjust the weights.

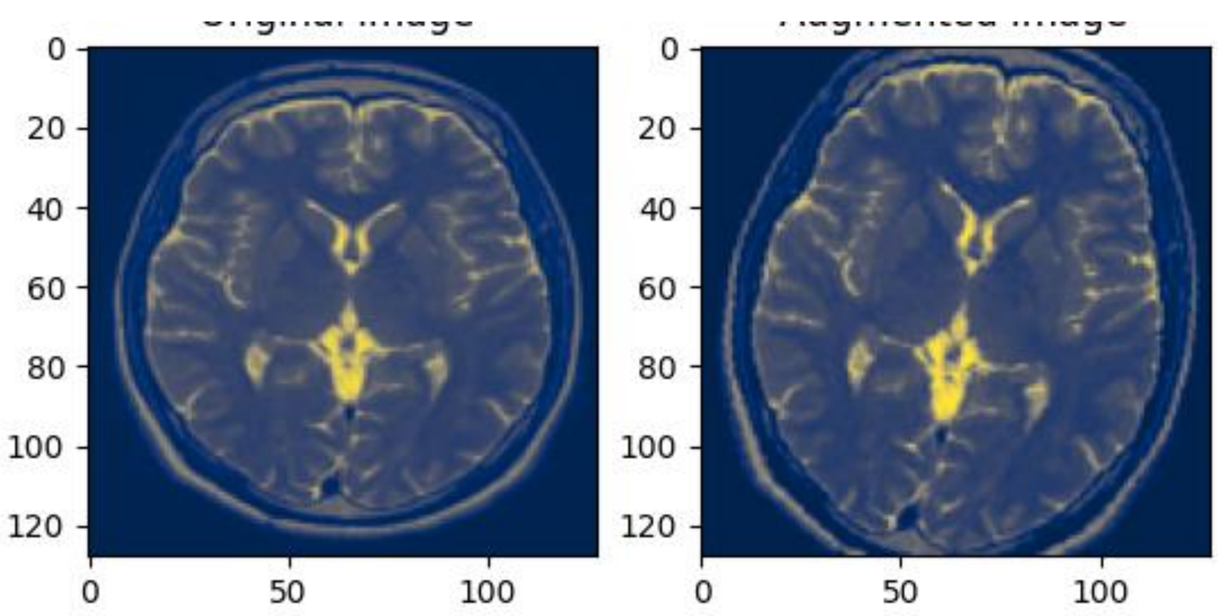
TRAINING NETWORK

Based on 253 images :

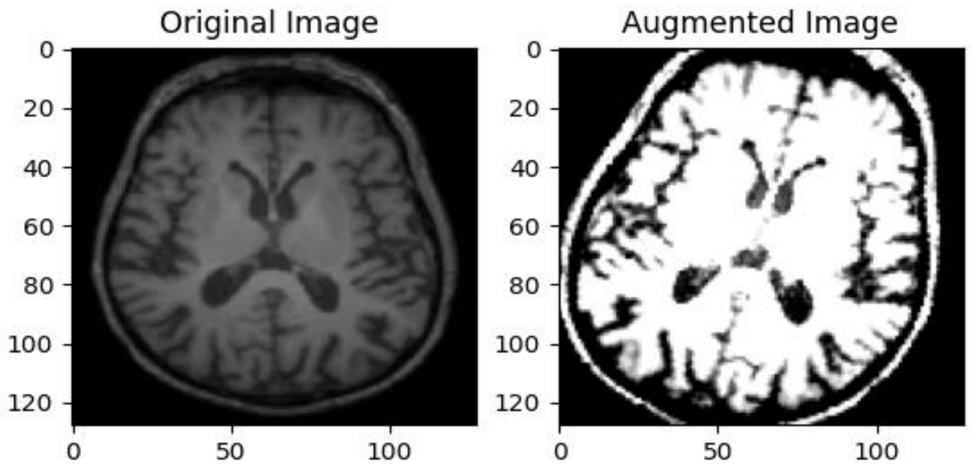
train_loss= 0.00429
train_acc=1.000
val_loss= 1.910
val_acc=0.692

Overfit

ADD DATA AUGMENTATION



- Enlarge our dataset to 512 images
  - Shrinking
  - Stretching
  - Rotating
  - Flipping
  - Cropping
  - Normalizing
  - Adding noises
  - Brightness / contrasts / Gamma corrections



AFTER DATA AUGMENTATION

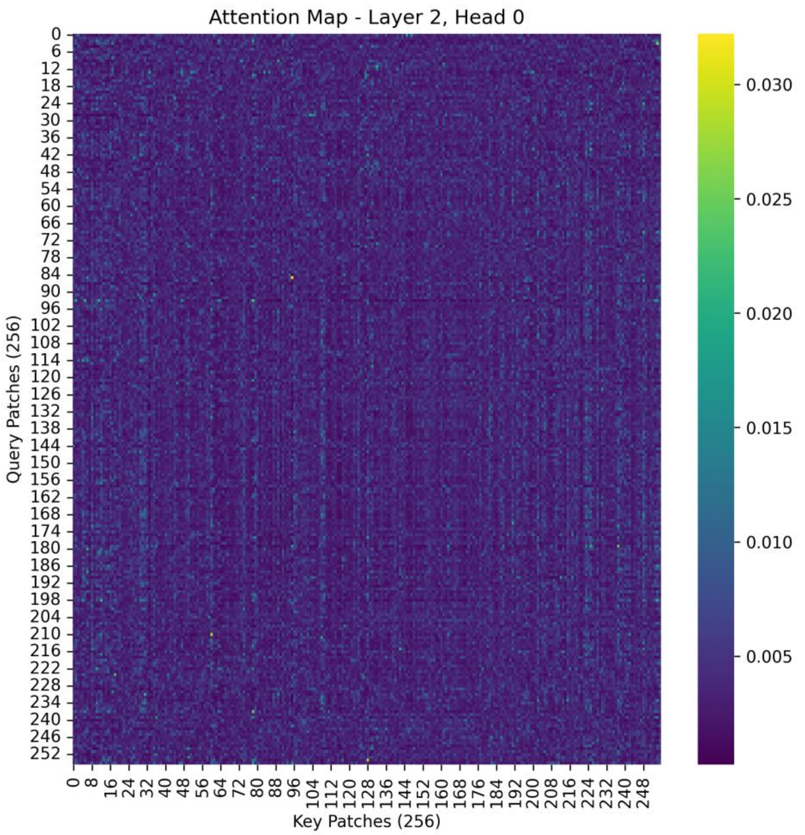
```
ViT results {'test': 0.9230769276618958, 'val': 1.0}
```

The good news :

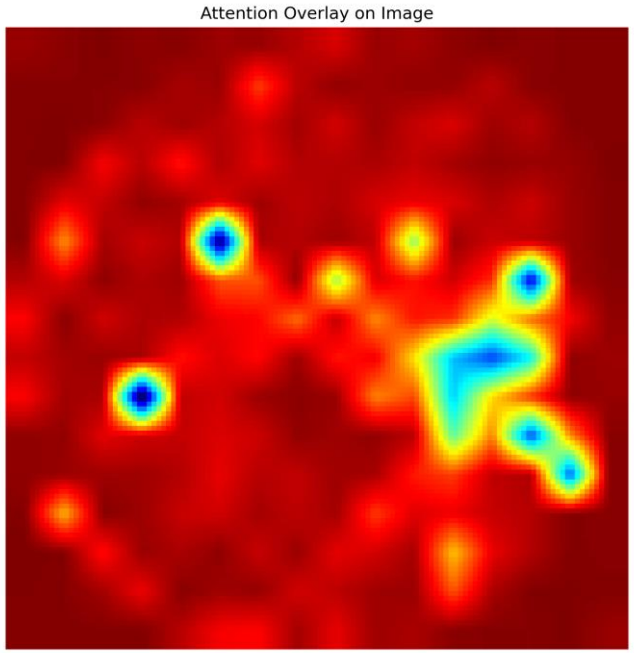
- Out model pinpoint the tumor in more than 90 % accuracy
- No overfit
- No false positives of brain lobes as tumors

ATTENTION MAP TO HEATMAP AS DEBUG HOOK

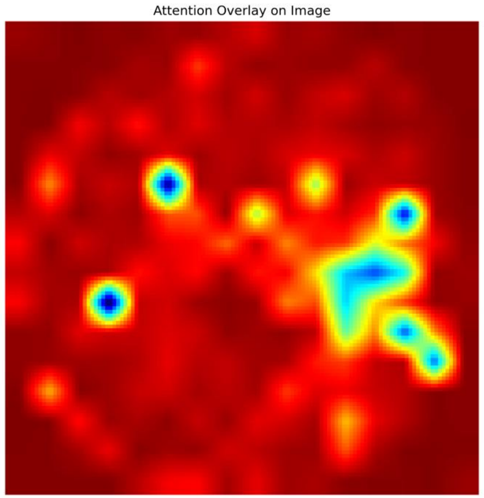
- Heatmap pinpoint the more important areas in the tested image
- Helps the developer to figure out if hir model focus the right areas in image

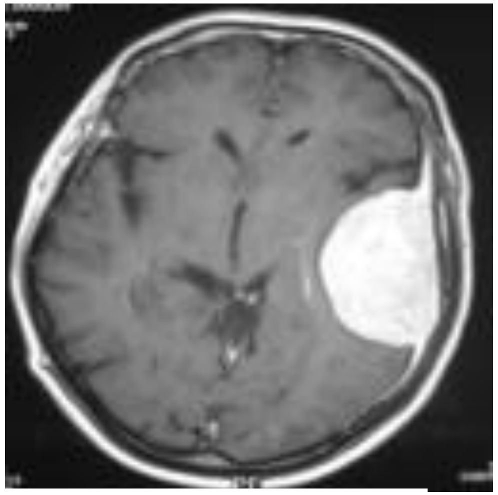


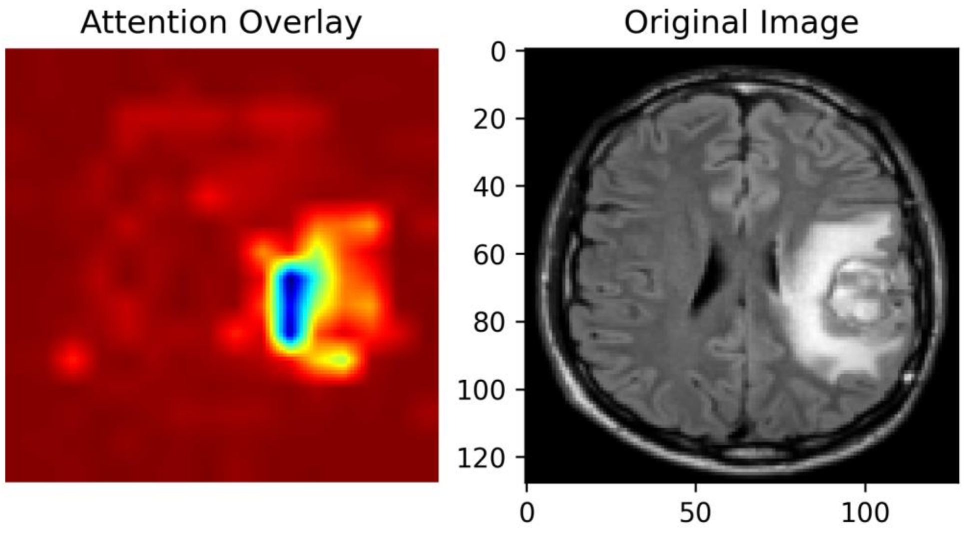
Some mathematical operation

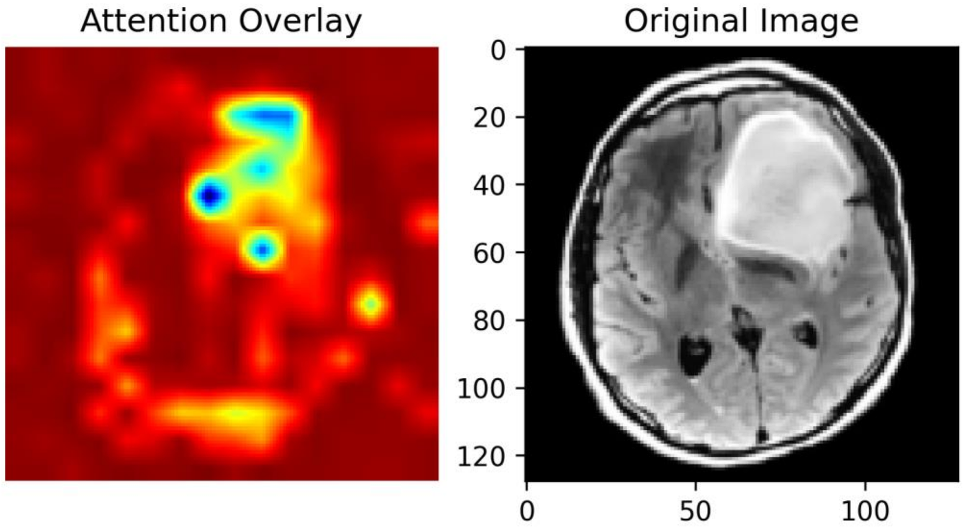


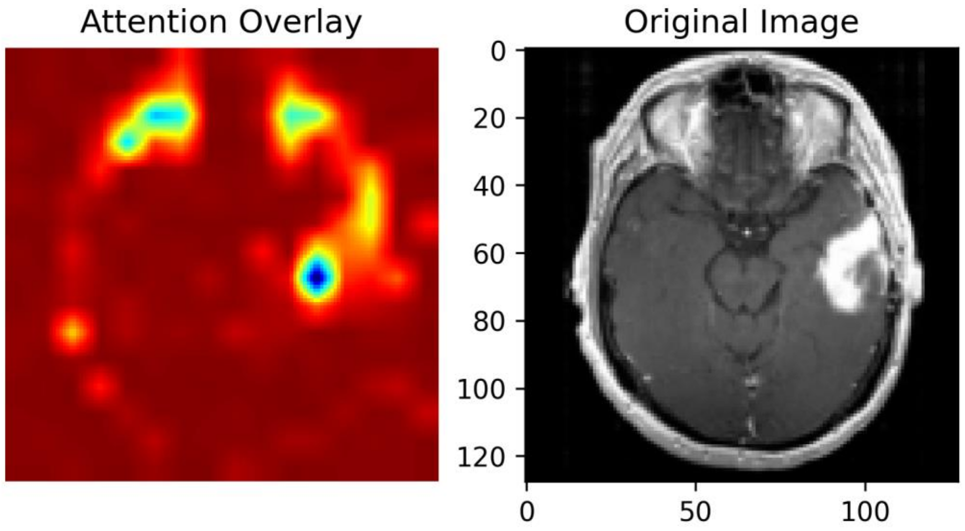
VISUALIZE HEATMAP



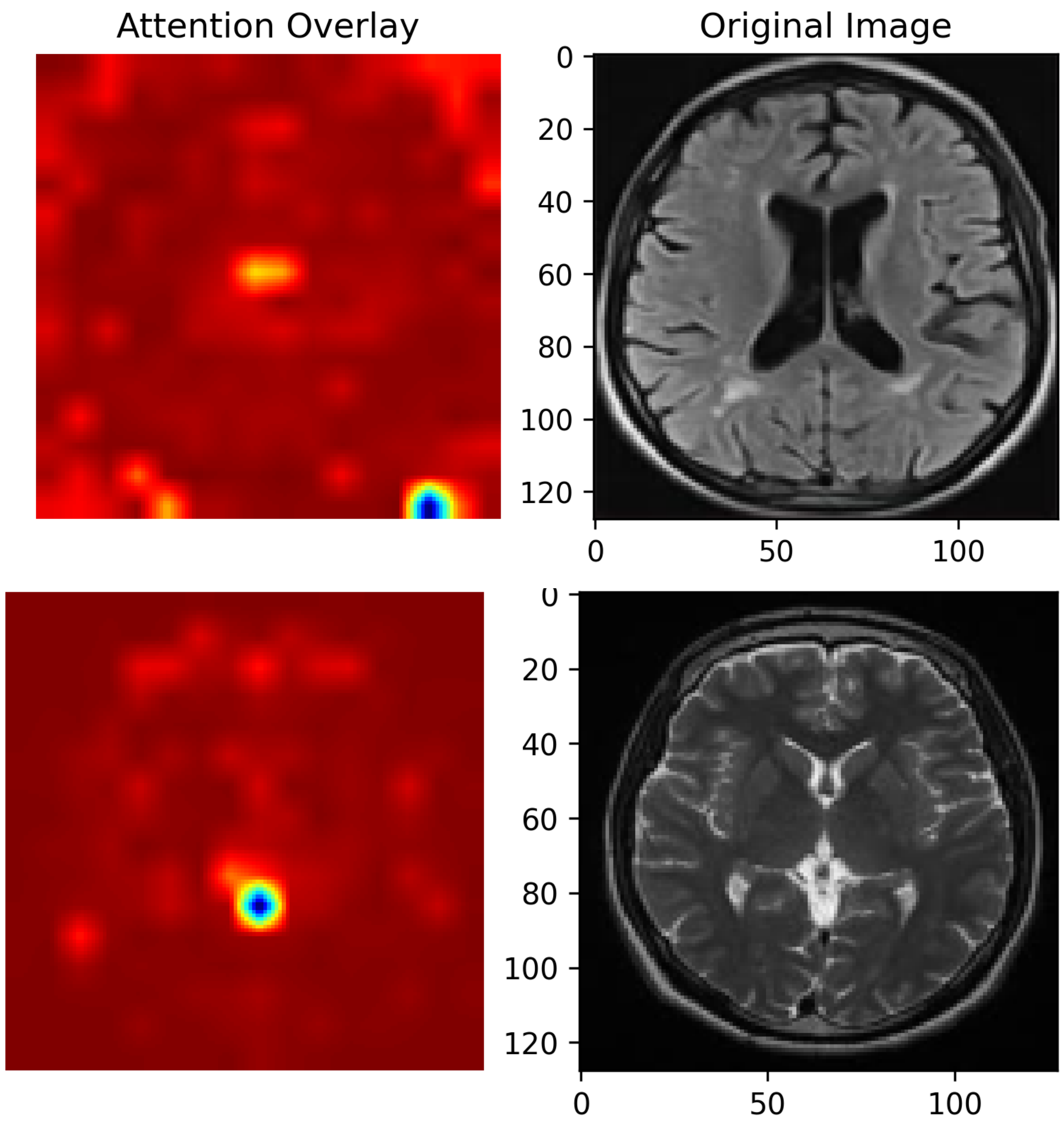






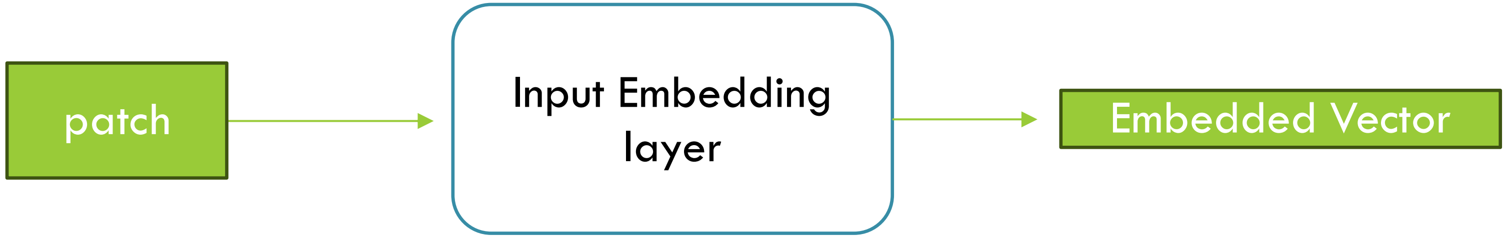


HEATMAP FOR NON DETECTED



QUESTION #3

- This is supervised learning problem
- Our dataset is MRI images within yes/no classification
- We have denoted that embedding layer importance to provide patch vectorization is critical



- But input layer embedding has never been trained ? So how it knows to initiate these vectors ?

QUESTION #3

- During training, the model computes the **final classification loss** (for the whole image — yes or no tumor).
- **backpropagation** computes gradients **all the way back** through the Transformer layers **and also through the embedding layer**