



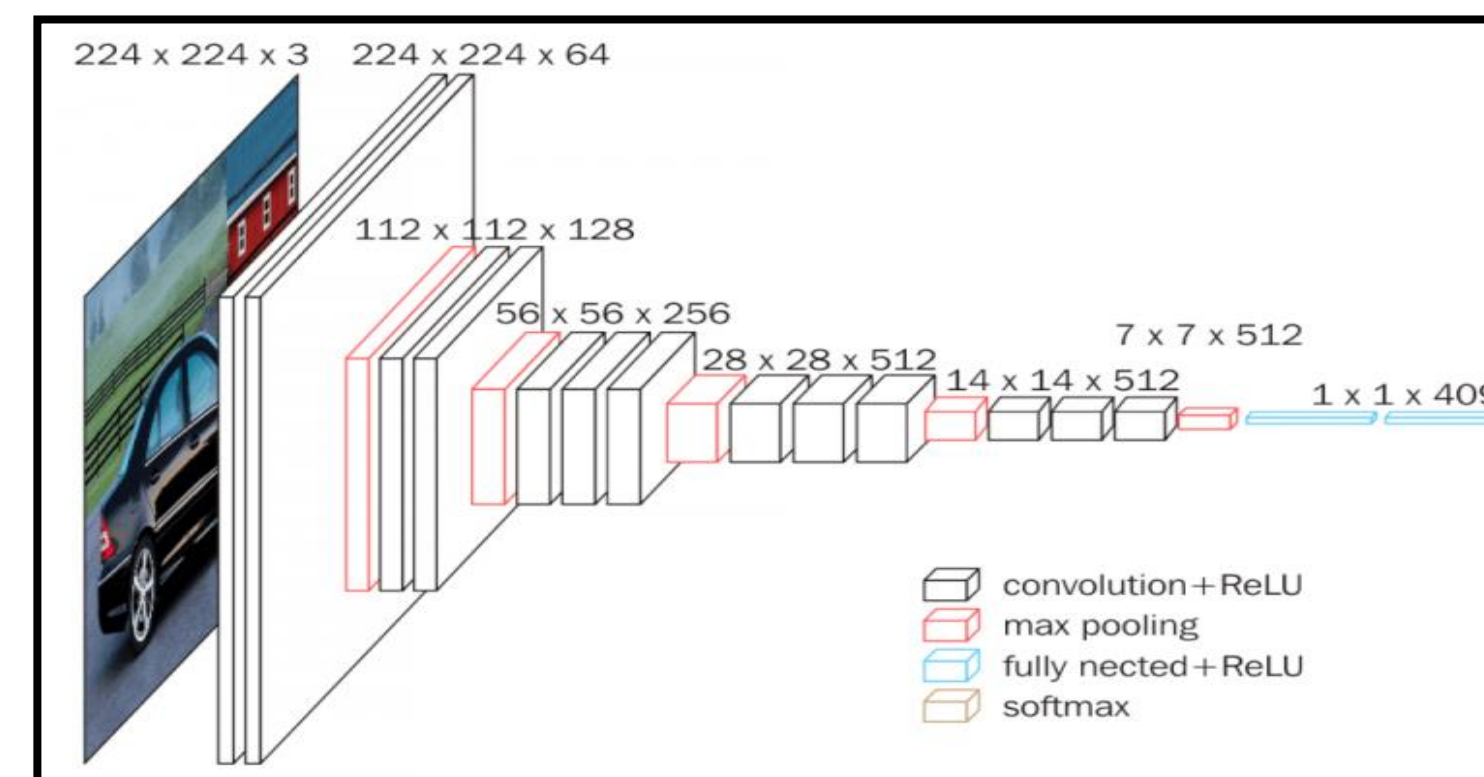
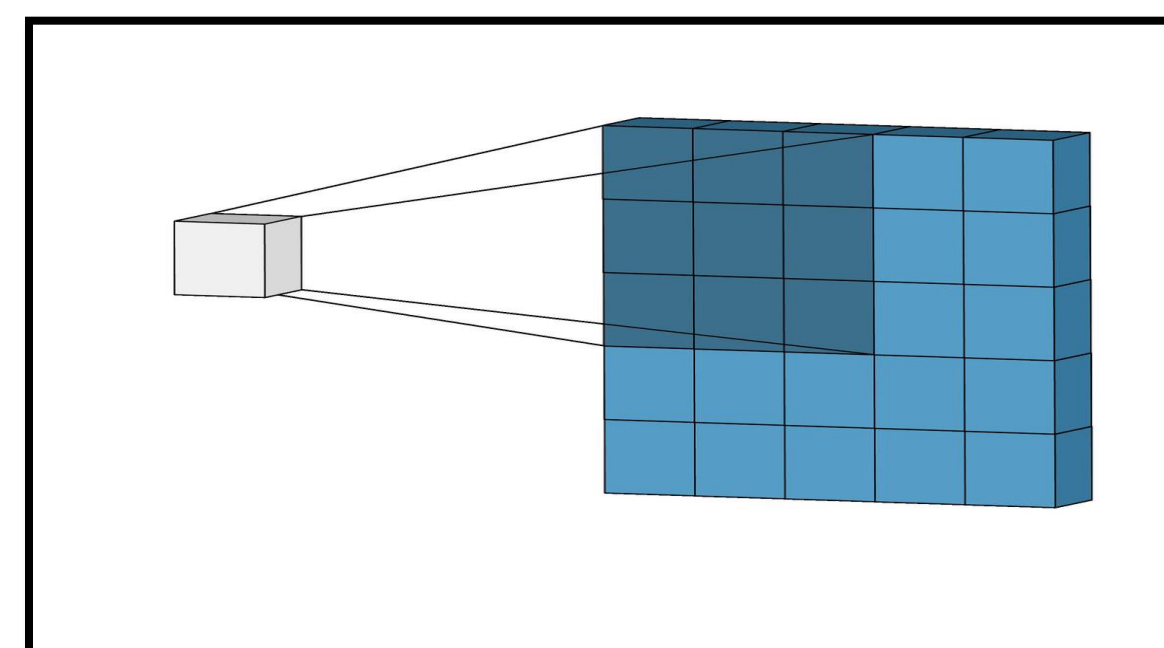
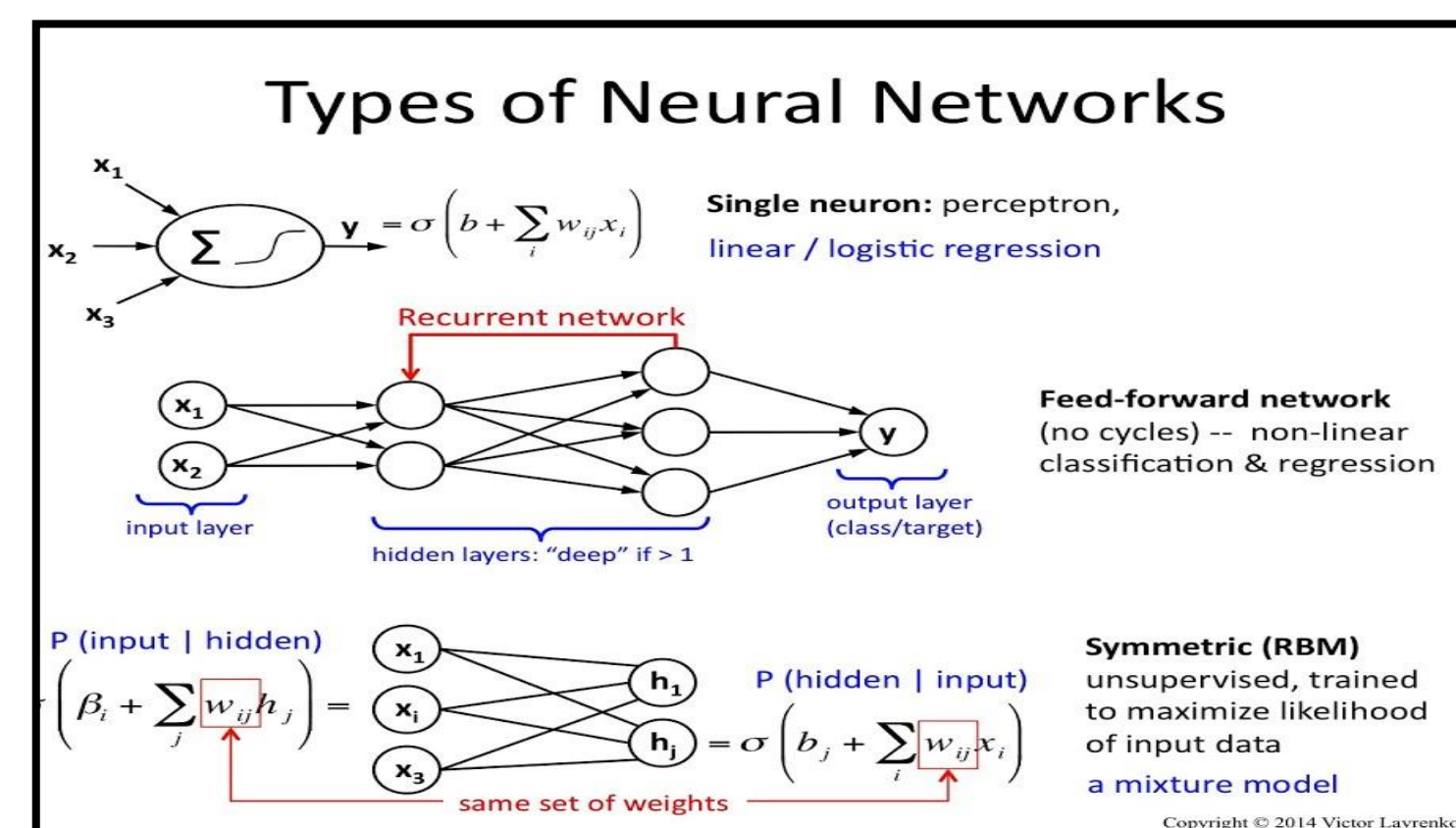
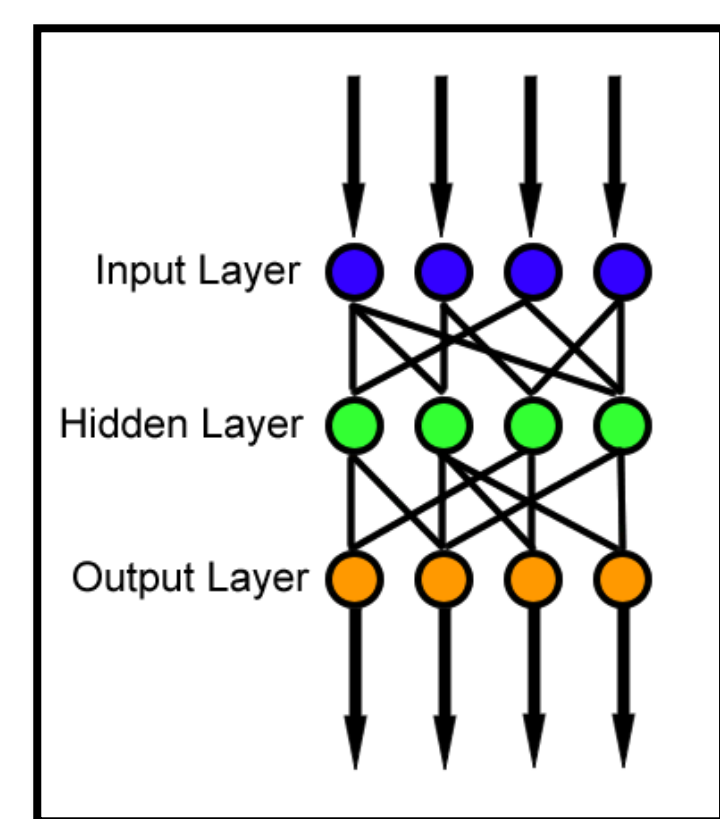
# VISUALISATION OF ARTIFICIAL INTELLIGENCE MODEL FOR CLASSIFICATION OF COLORECTAL CANCER

Aniruddha Mundhada, Anurag Mundhada, Lawrence D'Cruze, Gokul Kripesh, Sandhya Sundaram  
SRIHER Chennai India | Insane.ai Bangalore India



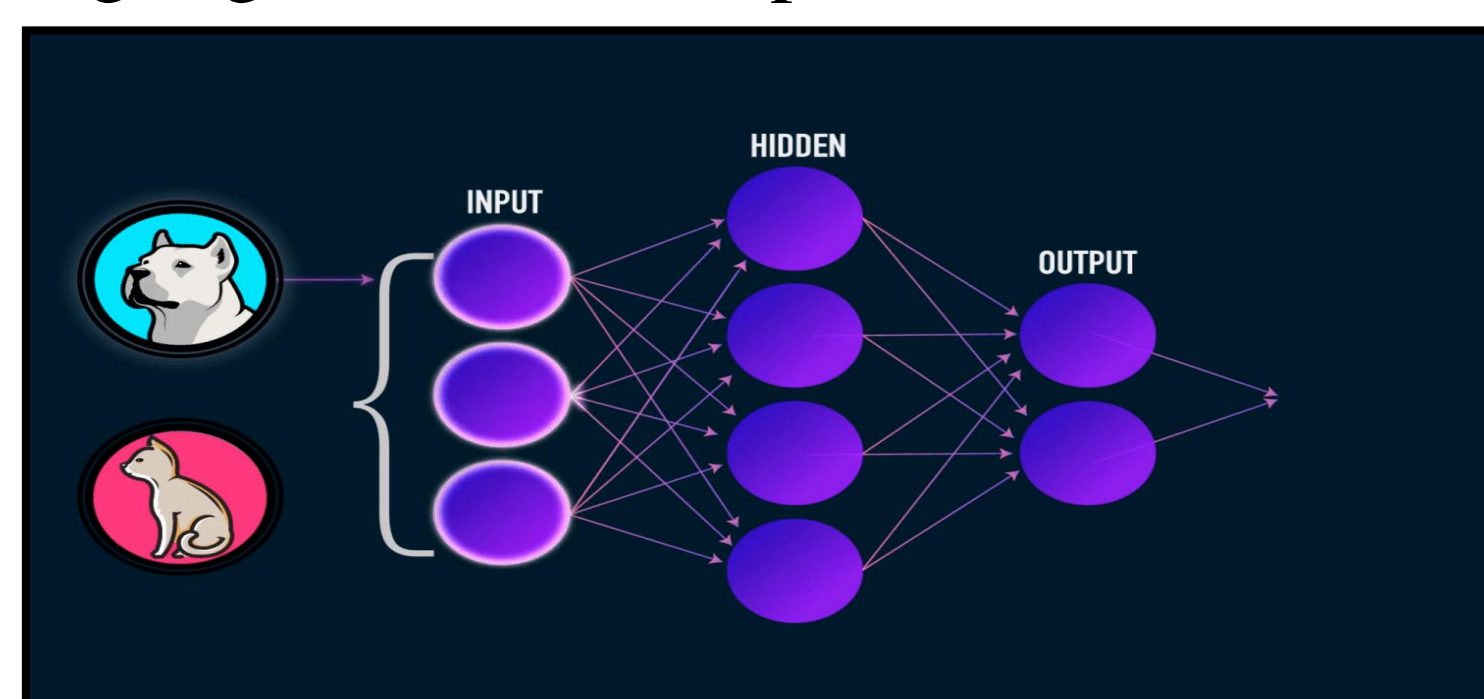
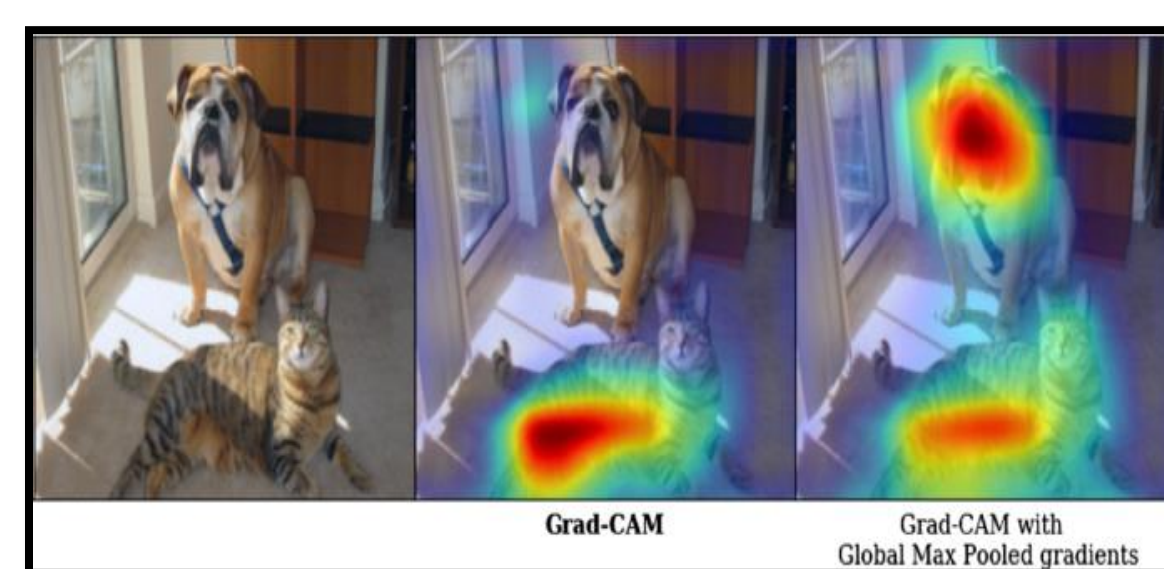
## Introduction

- Deep learning models learn very generic features at initial layers, which makes it possible to reuse a network trained on task A for task B
- De-facto pre-training on ImageNet, a large dataset for generic image classification having 1000 categories
- Pre-trained network outputs a *representation* of the image, which is easier for computers to further classify into new target classes
- With pre-training, need 100-500 examples of each new class for robust classification
- Knowledge learnt from image classification is *transferred* to new task of tissue classification



## Feature Visualisation

- Visualization of a Convolutional Neural Network (CNN) VGG16 at an intermediate layer using the Grad CAM technique.
- Data used was NCBI GDC repository of Colorectal adenocarcinoma slides [Total 5000 patches extracted from digitised FFPE slides]
- More than 100 examples of each class for training
- Grad Cam technique which highlights the feature points in red

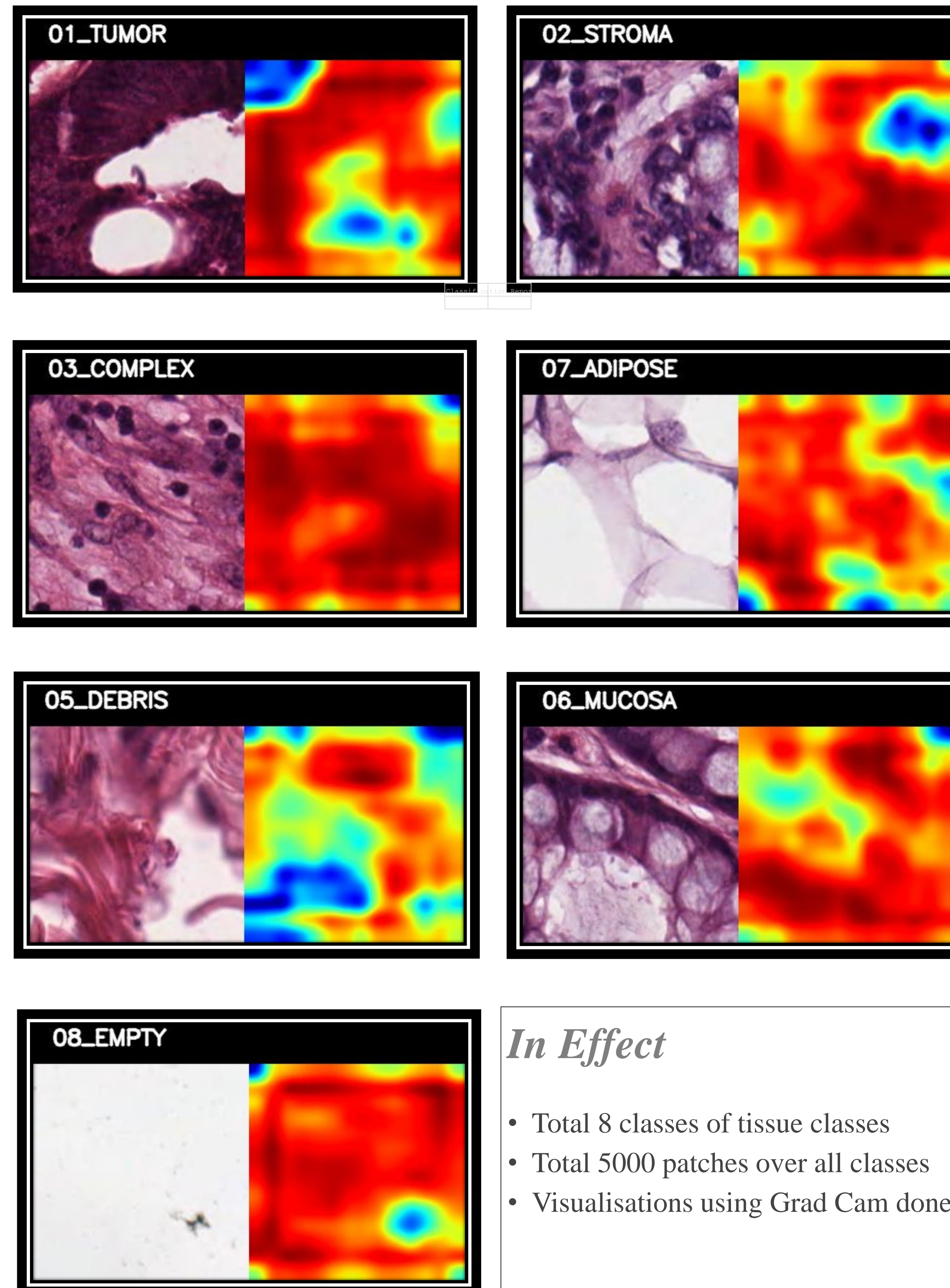


Grad Cam Technique for visualisation of CNN

## Tissue Classification Using CNNs

- There are 4 classes of tissue namely- tumor, adipose, debris and mucosa.
- Other classes also included: Stroma, complex, lymphocyte and stroma

## Convolutional Neural Network Visualisations

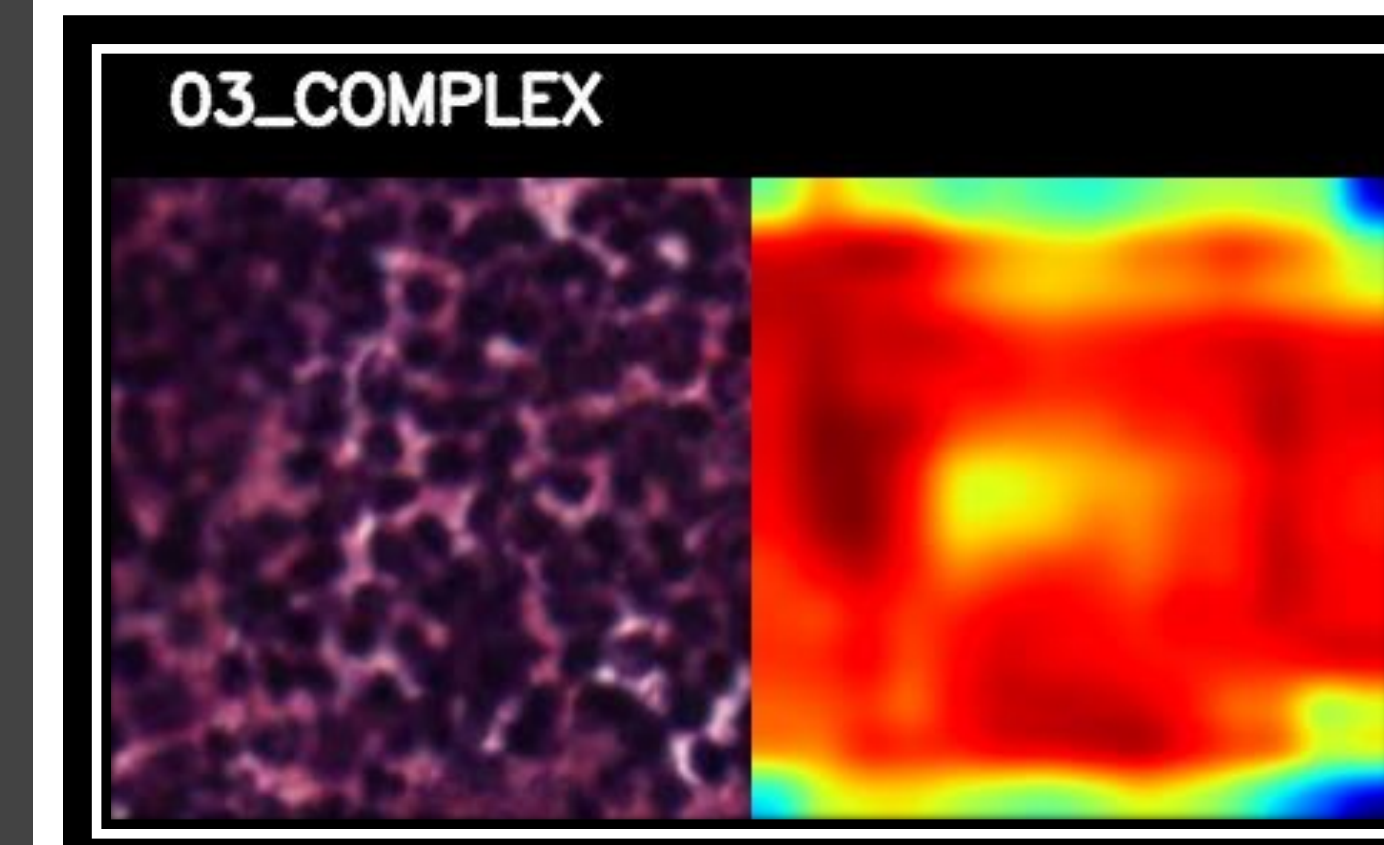
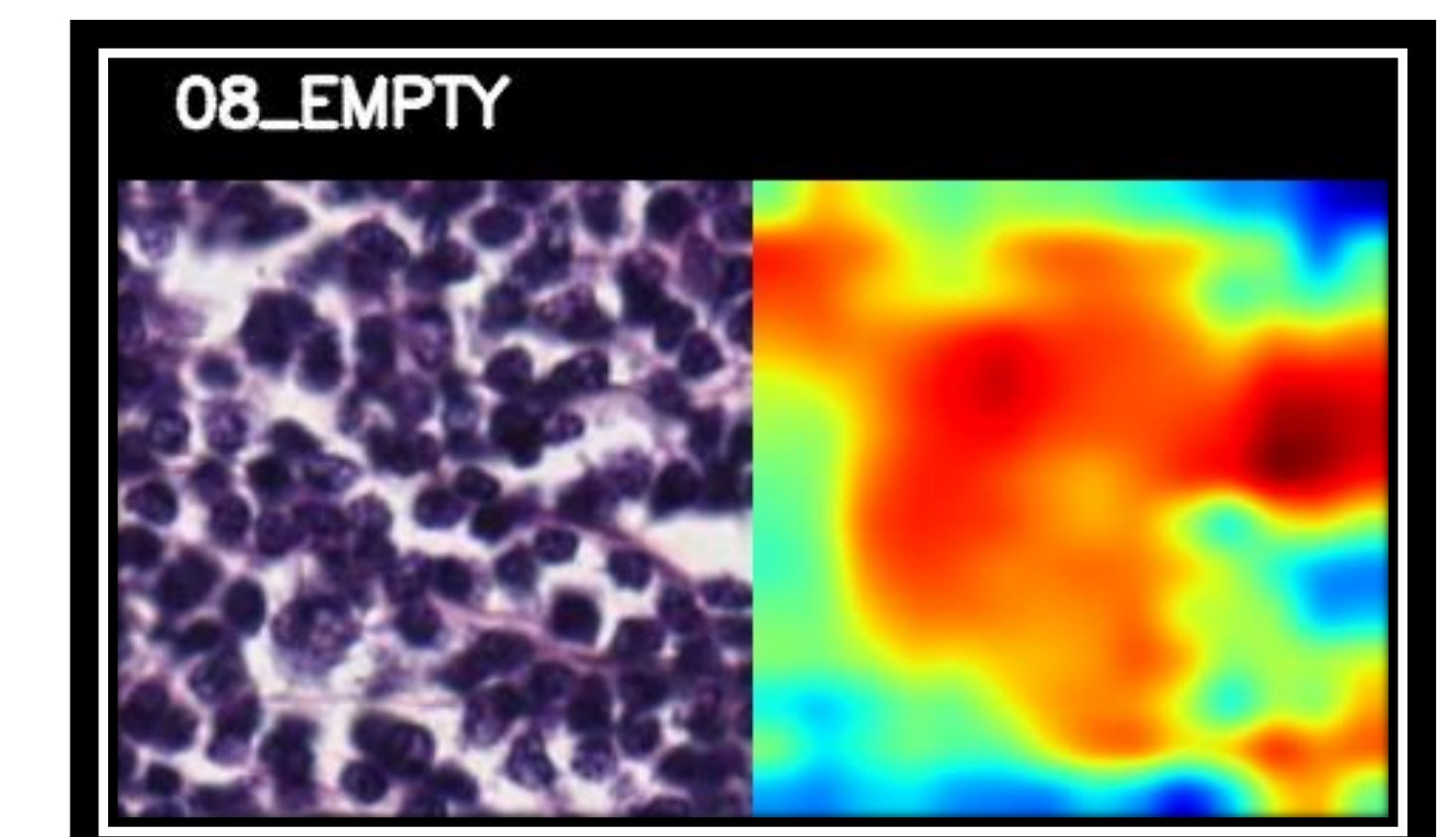
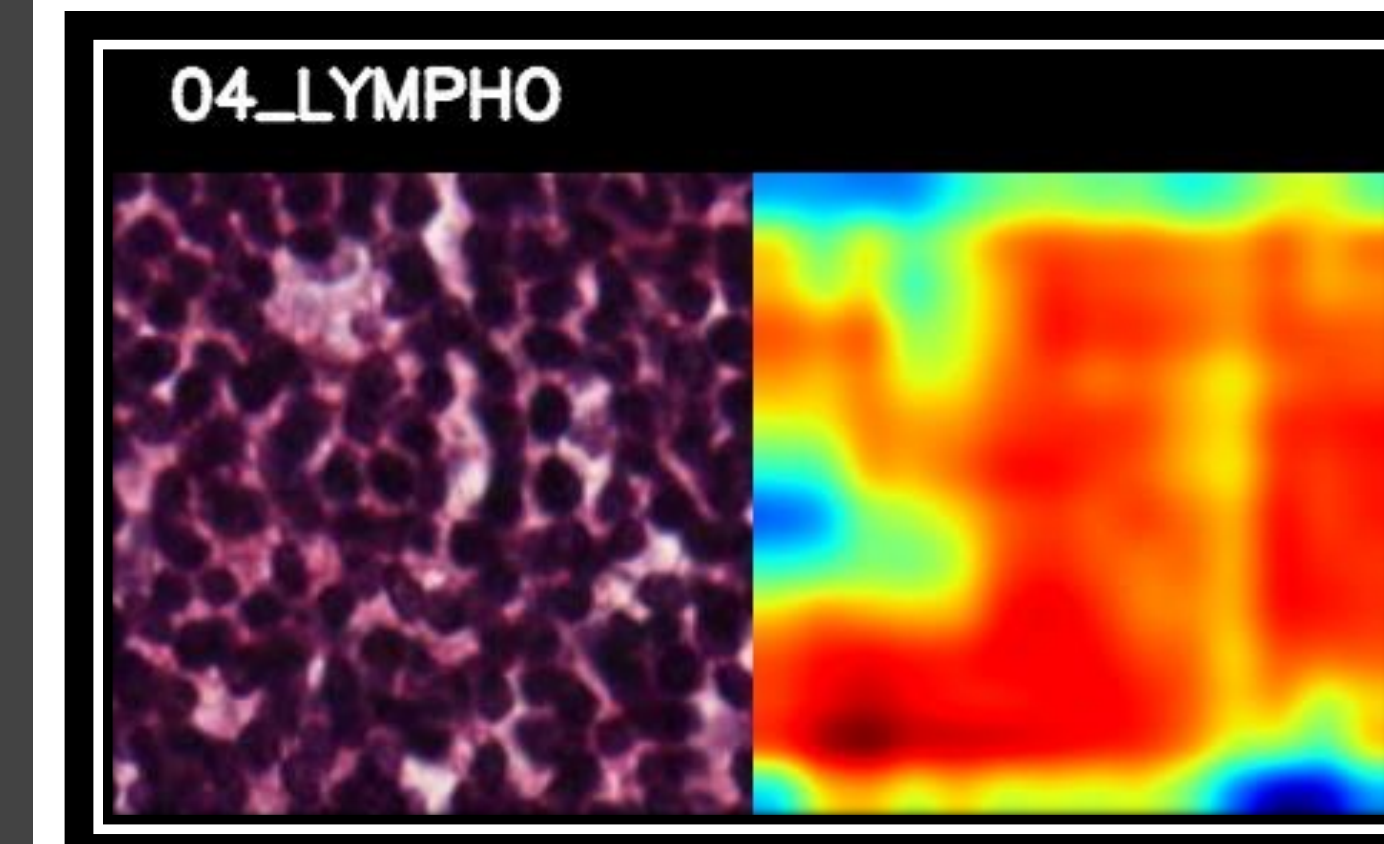


### In Effect

- Total 8 classes of tissue classes
- Total 5000 patches over all classes
- Visualisations using Grad Cam done

## Interpretation Errors

- Classify • Regress • Segment
- We need a lot of data + hardware to train deep models
- Pre-trained models can be used to achieve a really good performance in classification and regression



	Precision	Recall	F1 Score	Support
Accuracy			0.63	247
Macro Average	0.63	0.63	0.63	247
Weighted Average	0.63	0.63	0.63	247

Wrong Interpretation of Tumor Class As Lymphocytes or Empty or Complex Classes

	Precision	Recall	F1 Score	Support
01_TUMOR	0.68	0.69	0.69	32
02_STROMA	0.74	0.73	0.74	39
03_COMPLEX	0.77	0.68	0.67	26
04_LYMPHO	0.75	0.75	0.75	27
05_DEBRIS	0.73	0.74	0.74	28
06_MUCOSA	0.75	0.73	0.74	31
07_ADIPOSE	0.74	0.72	0.73	37
08_EMPTY	0.67	0.67	0.67	27

### In Summary

- Precision, recall and F1 score reported for all 8 classes
- Tumor class displays a low F1 score
- This suggests that a human + machine interpretation will supersede either one
- Best case use as a screening tool

## References

1. VGG16 <https://neurohive.io/en/popular-networks/vgg16/>
2. Kather JN, Weis CA, Bianconi F, Melchers SM, Schad LR, Gaiser T, Marx A, Zollner F: Multi-class texture analysis in colorectal cancer histology (2016), Scientific Reports (in press)
3. Selvaraju, R.R., Cogswell, M., Das, A. et al. Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. *Int J Comput Vis* **128**, 336–359 (2020). <https://doi.org/10.1007/s11263-019-01228-7>
4. Intuitively Understanding Convolutions for Deep Learning <https://towardsdatascience.com/intuitively-understanding-convolutions-for-deep-learning-1f6f42faee1>
5. Code developed [https://colab.research.google.com/drive/1zH94dNwXN5nxOIn7nJ\\_XgR7QeZ0bt97P?usp=sharing](https://colab.research.google.com/drive/1zH94dNwXN5nxOIn7nJ_XgR7QeZ0bt97P?usp=sharing)