02-718 Project

Tumor Detection From Histopathology Images

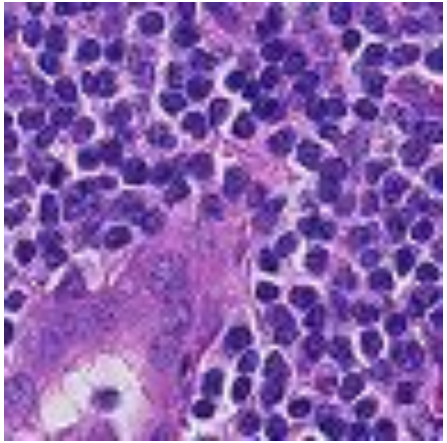
Team members :

- Arjun Sarathi (asarathi)
- Chris Lee (chrisl2)
- Haodong Liu (haodong2)

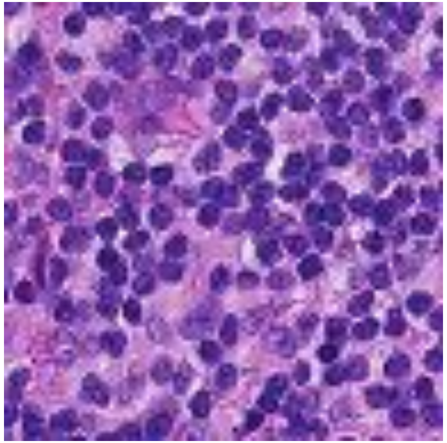
Image Source: https://wallpapercave.com/w/wp4708095

Histopathology

Tumorous Lymph Tissue



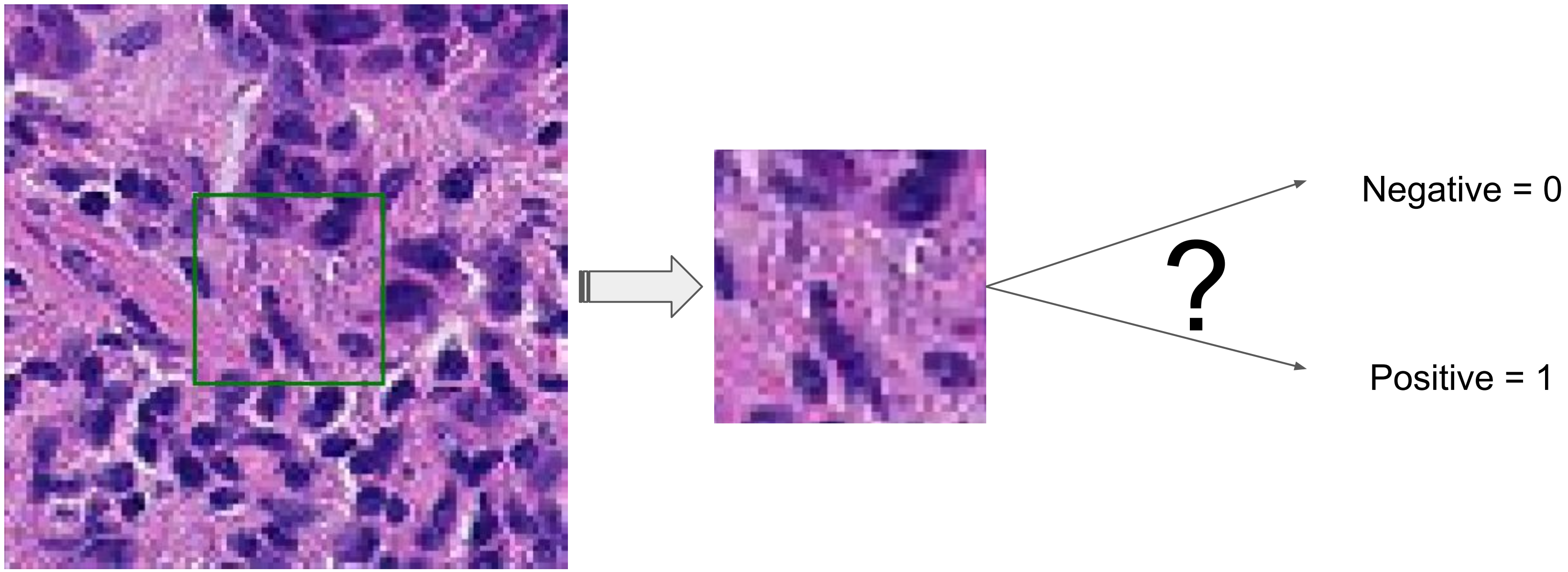
Healthy Lymph Tissue



Original tissue images (PCAM) from: https://github.com/basveeling/pcam & https://www.kaggle.com/c/histopathologic-cancer-detection/data

Objective

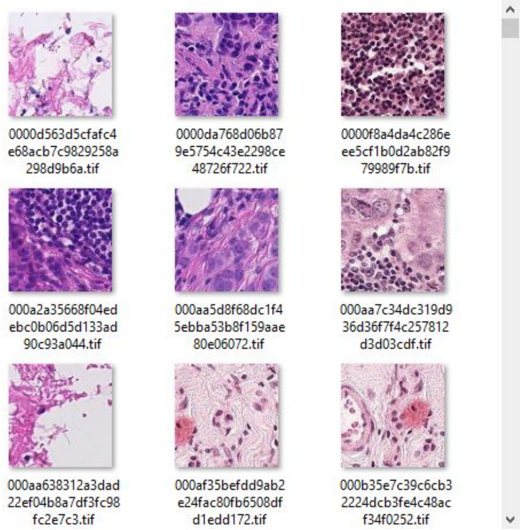
Given a 96x96 px image, is there at least one pixel of tumor tissue in the center 32x32 px region?



Original tissue images (PCAM) from: https://github.com/basveeling/pcam & https://www.kaggle.com/c/histopathologic-cancer-detection/data

Data Acquisition

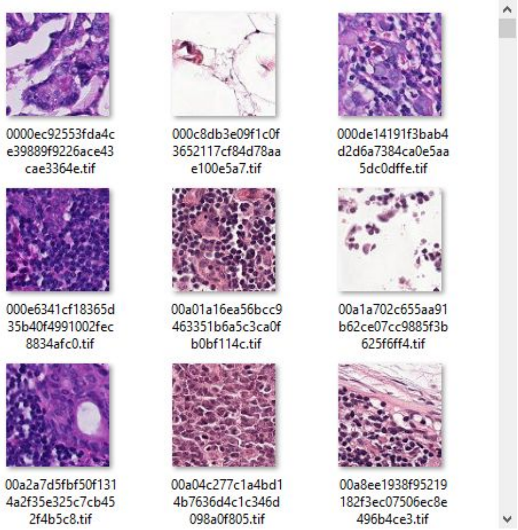
Training Data



Training Labels

id	label
f38a6374c348f90b587e046aac6079959adf3835	0
c18f2d887b7ae4f6742ee445113fa1aef383ed77	1
755db6279dae599ebb4d39a9123cce439965282d	0
bc3f0c64fb968ff4a8bd33af6971ecae77c75e08	0
068aba587a4950175d04c680d38943fd488d6a9d	0
acfe80838488fae3c89bd21ade75be5c34e66be7	0
a24ce148f6ffa7ef8eefb4efb12ebffe8dd700da	1
7f6ccae485af121e0b6ee733022e226ee6b0c65f	1
559e55a64c9ba828f700e948f6886f4cea919261	0
8eaaa7a400aa79d36c2440a4aa101cc14256cda4	0
a106469bbfda4cdc5a9da7ac0152927bf1b4a92d	0
c3d660212bf2a11c994e0eadff13770a9927b731	1
a1991e73a9b676faddd2bd47c39754b14d1eb923	0
08566ce82d4406f464c9c2a3cd014704735db7a9	0
94fa32b29cc1c00403176c0795fffa3cfaa0f20e	1
f416de7491a31951f79b3cee75b002f4d1bf0162	0
a1c001f6b242c72d3066f15ac6eb059ea72d30ba	0
0b820b71670c039dd0a51333d1c919f471a9e940	1
730431efa2f79927156dcc4382819e9a6cc2c5bb	0
d34af1e7500f2f3de41b0e6fdeb2ed245d814590	1

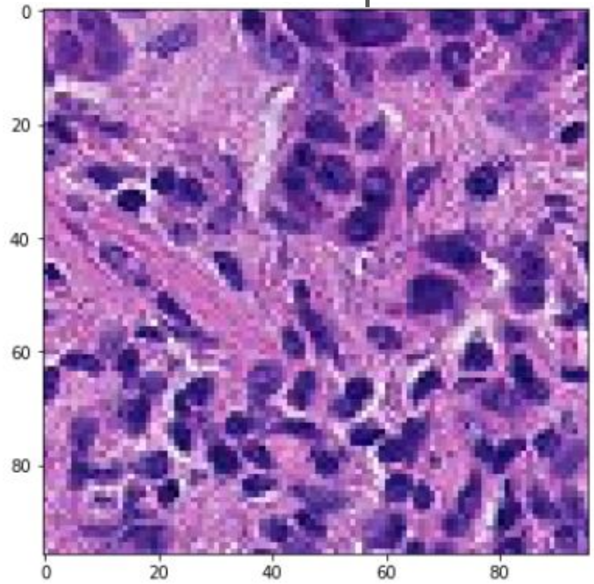
Test Data



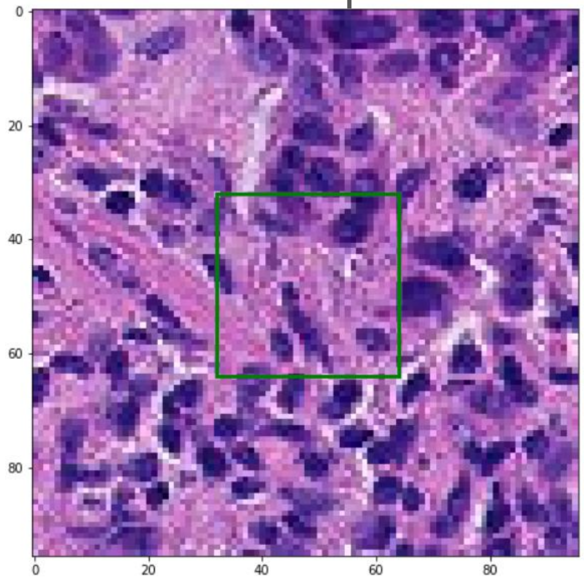
Original tissue images (PCAM) from: https://github.com/basveeling/pcam & https://www.kaggle.com/c/histopathologic-cancer-detection/data

Data Processing - Cropping

Original input image:
96x96 px



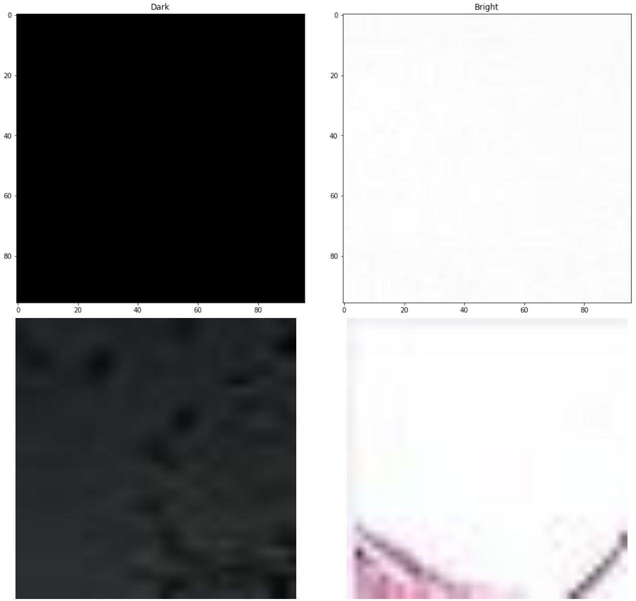
Cropped section we will train and predict:
32x32 px

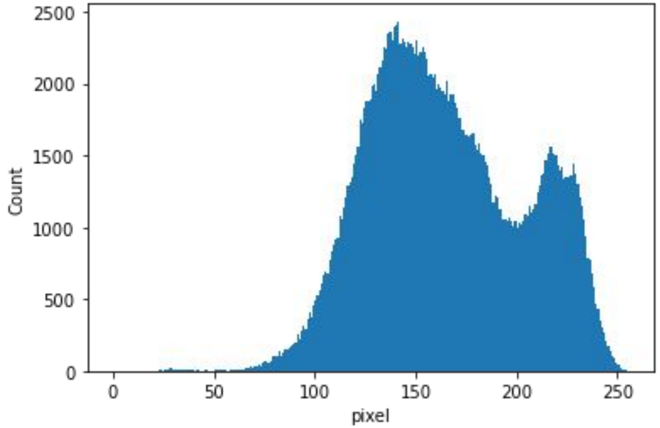


Original tissue images (PCAM) from: https://github.com/basveeling/pcam & https://www.kaggle.com/c/histopathologic-cancer-detection/data

Data processing - Brightness filtering

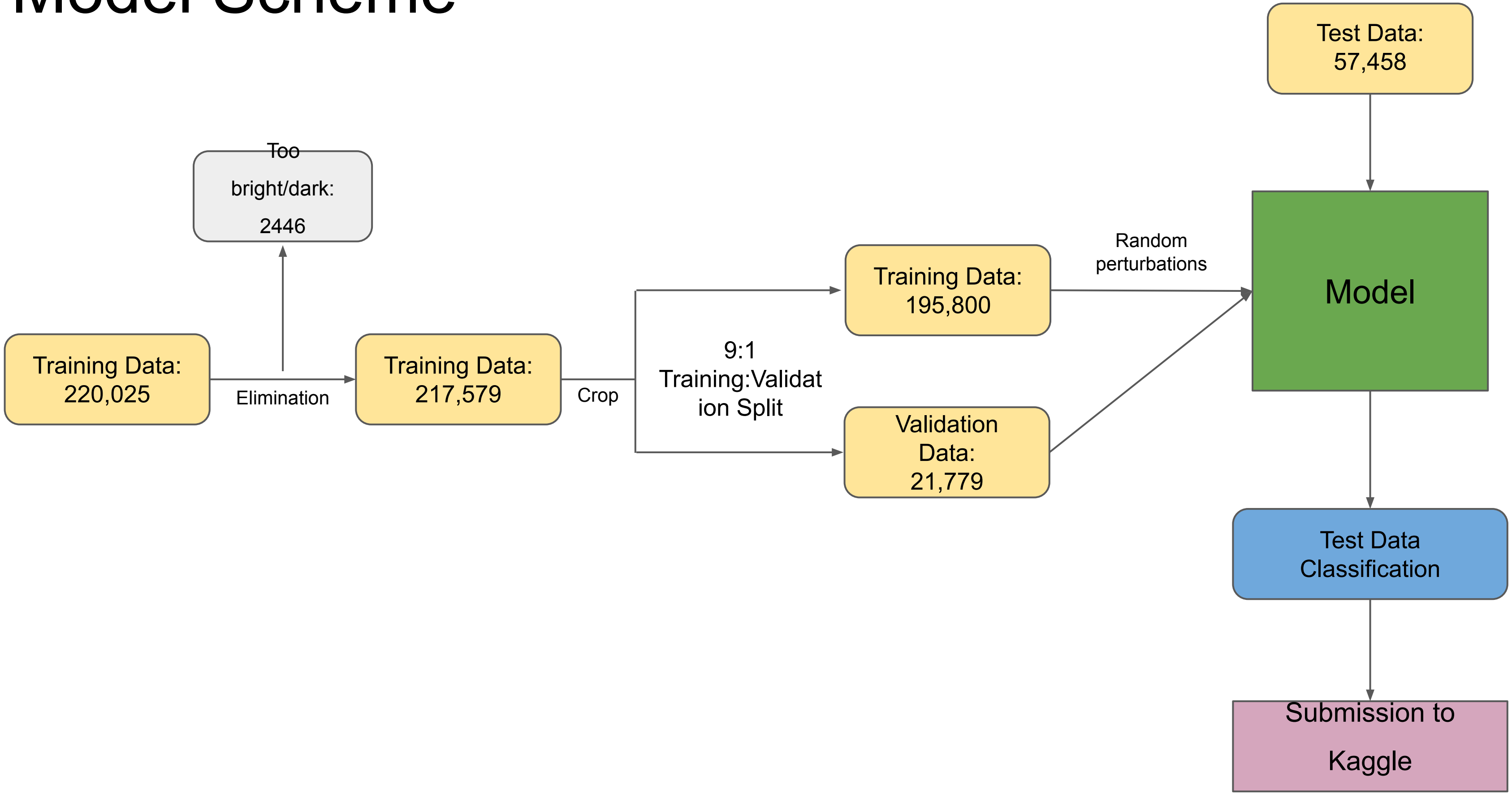
Removing images that were too bright or dark. A ‘pixel’ score close to 0 means an image is too dark, while one close to 255 means it is too bright





Original tissue images (PCAM) from: https://github.com/basveeling/pcam & https://www.kaggle.com/c/histopathologic-cancer-detection/data

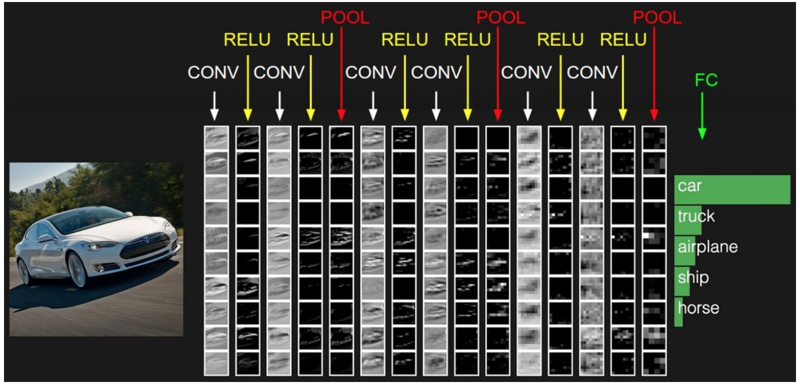
Model Scheme

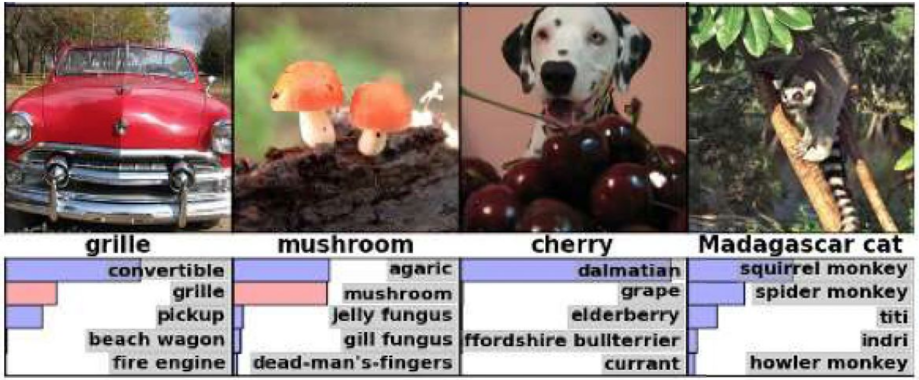


Deep learning approach to image classification

Deep learning methods have became popular in past ten years.
Various models have been used in image recognition tasks and competitions.

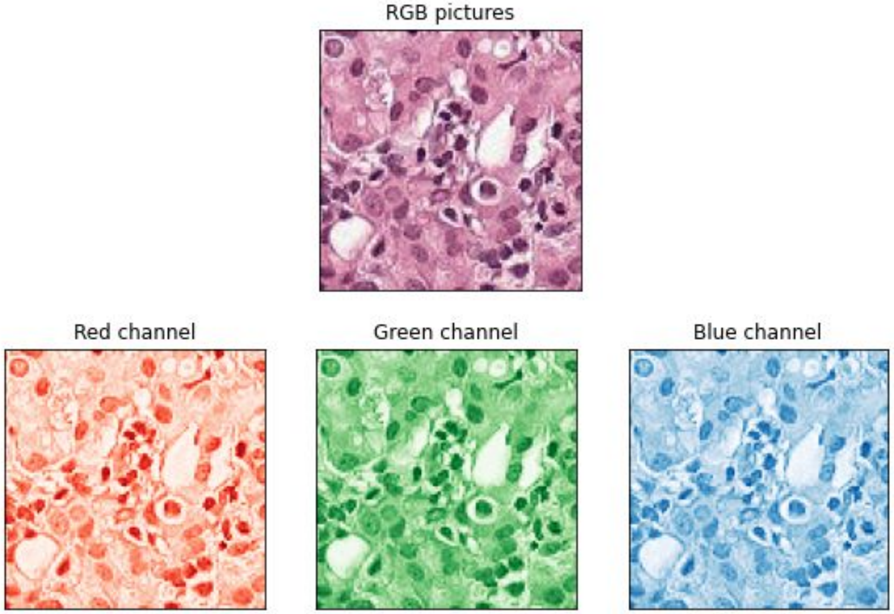
Below is the input and output labels from a deep convolutional neural network on ImageNet pictures.





Example picture from: https://cs231n.github.io/convolutional-networks/
Krizhevsky, A., Sutskever, I. and Hinton, G. E. “ImageNet Classification with Deep Convolutional Neural Networks”

Convolutional Neural Network: The data tensor



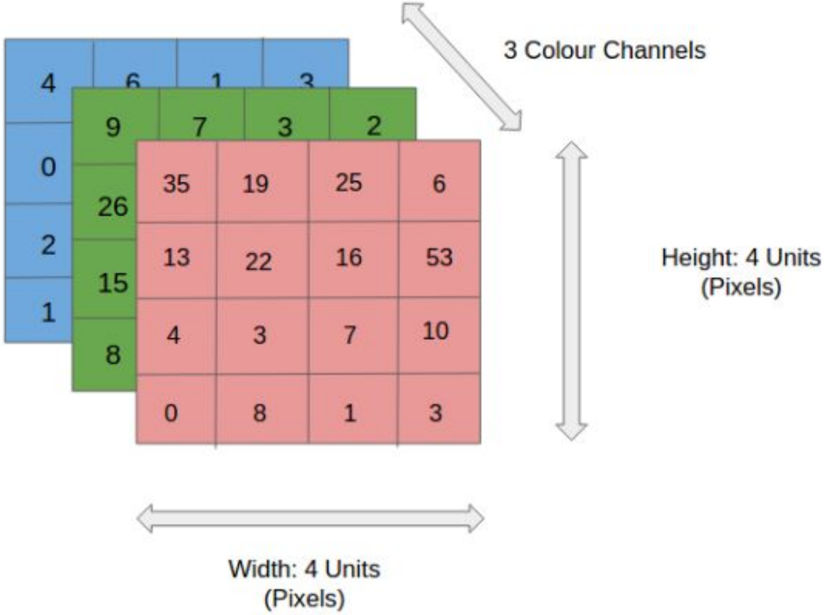
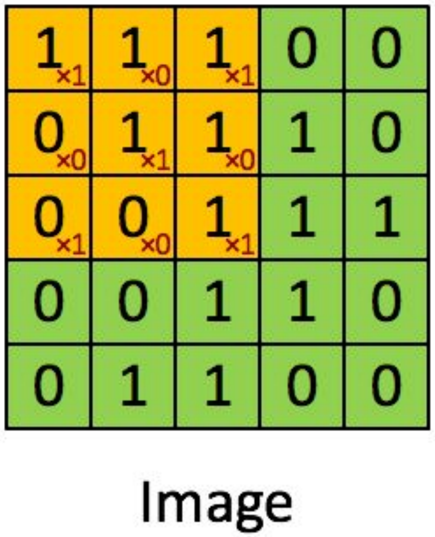
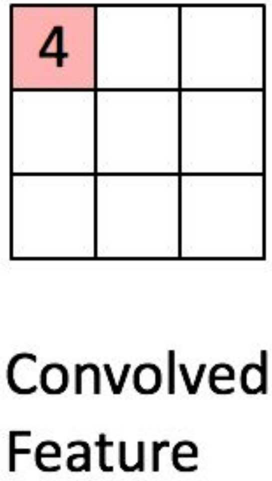


Image Source: Medium blogpost: A Comprehensive Guide to Convolutional Neural Networks — the ELI5 wa

Convolutional Neural Network: Convolution Layer

```
Kernel/Filter, K =

1  0  1
0  1  0
1  0  1
```





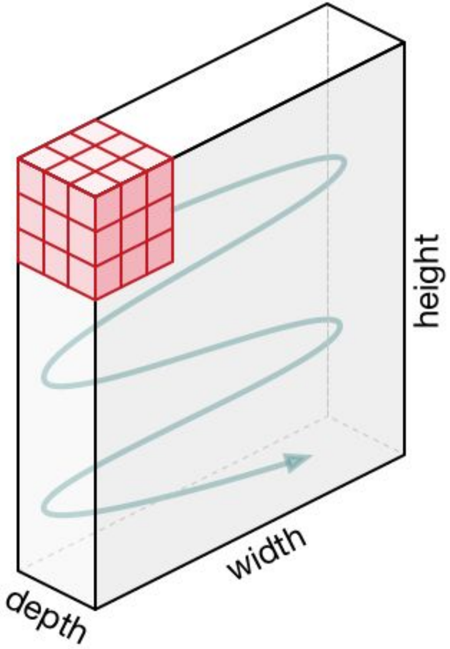
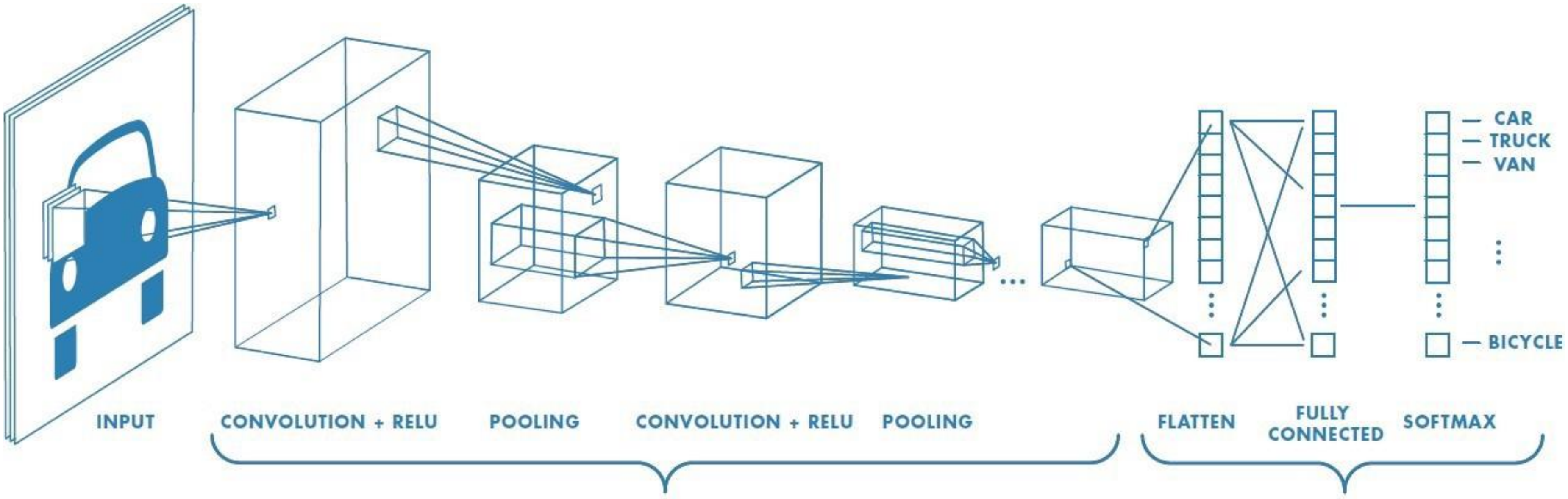


Image Source: Medium blogpost: A Comprehensive Guide to Convolutional Neural Networks — the ELI5 wa

CNN: General Architecture



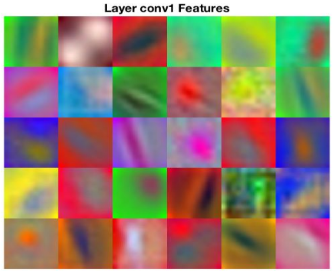
CNN layers: Feature Extraction **Linear layers: Classification**

Image Source: Medium blogpost: A Comprehensive Guide to Convolutional Neural Networks — the ELI5 wa

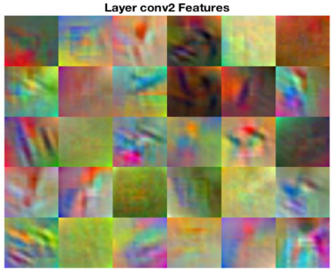
Convolutional Neural Network: Capture Features

Features encoded in each Conv layer

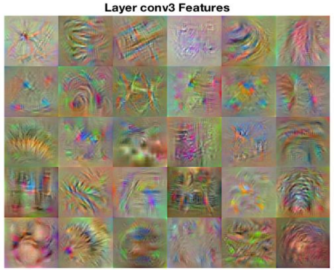
(a) Conv1



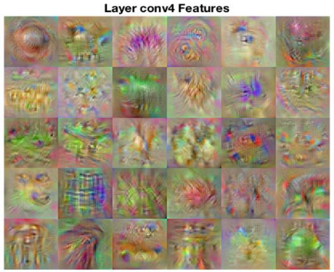
(b) Conv2



(c) Conv3



(d) Conv4



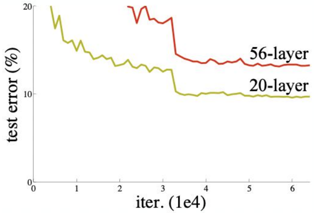
Encoded features:
In a trained CNN, Each layer does a “summary” of the input, and extract useful information and pass to subsequent layers.

As the data propagate in layers of CNN, the features scale changes from edge-level to concrete levels.

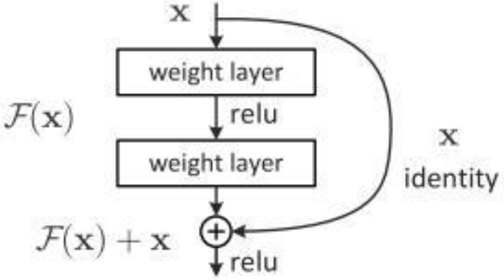
Image source : self generated for hw in course Neural computation

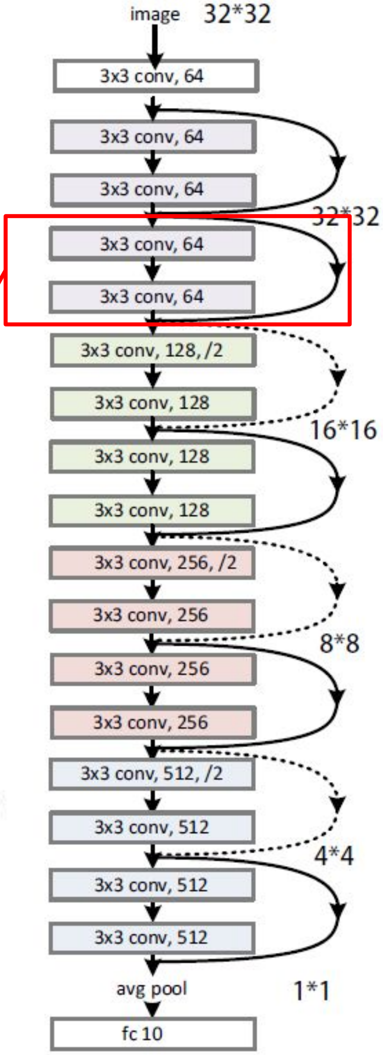
Residual Network (Resnet)

An problem in training **Deep** neural network: the training accuracy gets saturated at one point, and degrade quickly.



Residual learning block proposed by He[3]: The network learns the residual function *F* with a reference of previous input, instead of feature mapping directly on input.

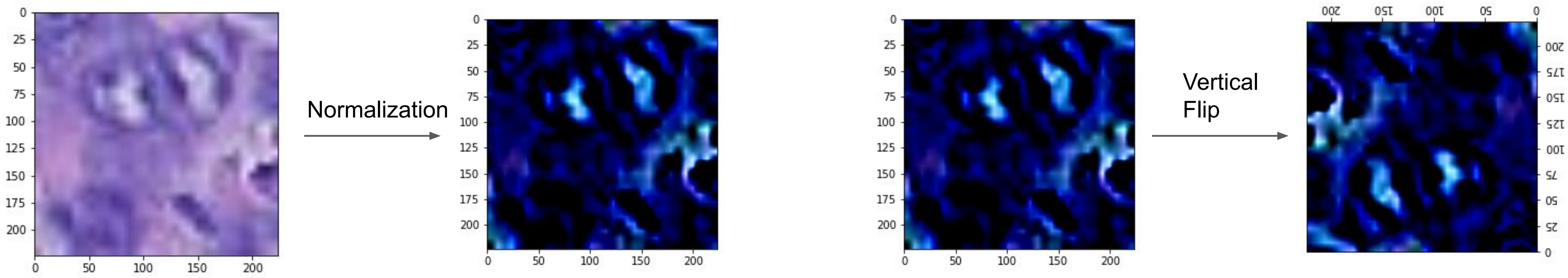




https://www.programmersought.com/article/68543552068/
He, Kaiming, et al. "Deep residual learning for image recognition."

Image transformation

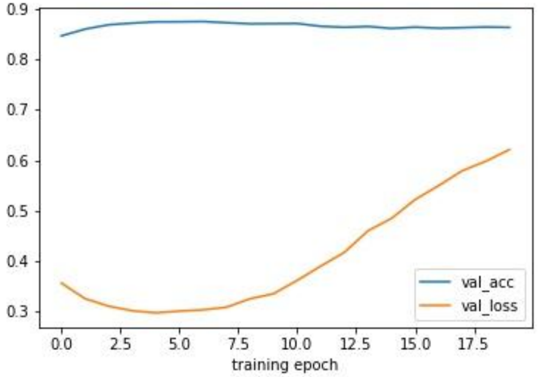
```
data_transforms = {
    transforms.Compose([
    transforms.CenterCrop(input_size),
    transforms.RandomHorizontalFlip(),
    transforms.RandomVerticalFlip(),
    transforms.ToTensor(),
    transforms.Normalize(rgb_channels_mean, rgb_channels_SD)
    ]),
```

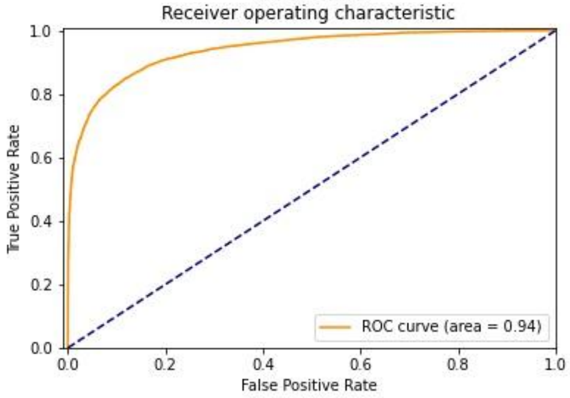


Original tissue images (PCAM) from: https://github.com/basveeling/pcam & https://www.kaggle.com/c/histopathologic-cancer-detection/data

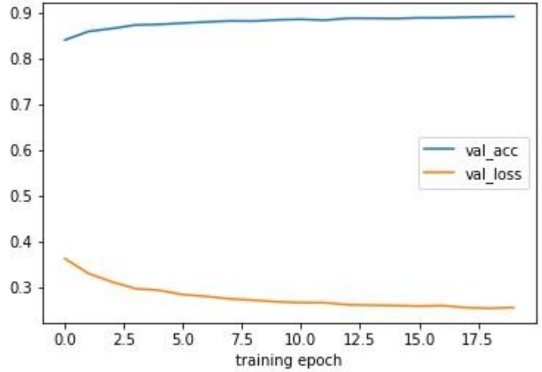
Training plot

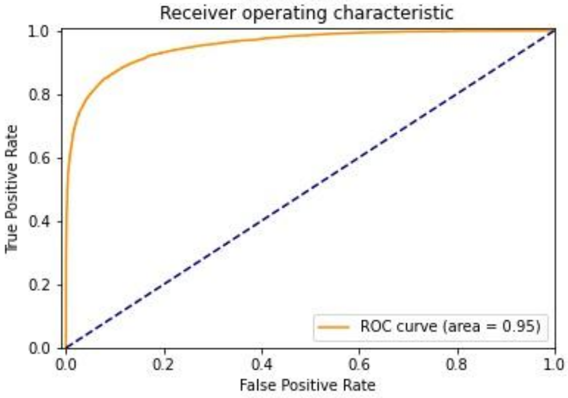
Resnet18





Resnet18 with Horizontal/Vertical flip

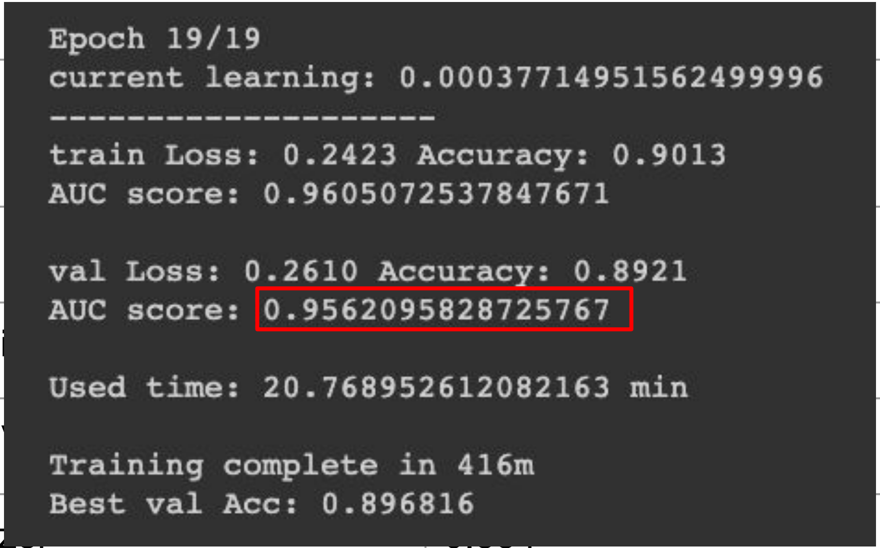





```
Epoch 19/19
current learning: 0.00037714951562499996
--------------------
train Loss: 0.0167 Accuracy: 0.9968
AUC score: 0.9998485619353557

val Loss: 0.6213 Accuracy: 0.8639
AUC score: 0.9280406778577234

Used time: 4.960741396745046 min

Training complete in 96m
Best val Acc: 0.875637
```

All training session use 20 epoches

Model	Extra Techn		Test AUC
Resnet18	/		0.89
Resnet18	Horizontal Fl		0.9054
Resnet18	Horizontal +		0.8981
Resnet18	Adam optimiz	[illegible]	0.9021



Other attempts to boost the performance:

1. **Fine tune different part of model, worse performance**

Fine tune the whole network
(Better Result)

```
Epoch 19/19
current learning: 0.00037714951562499996
--------------------
train Loss: 0.2423 Accuracy: 0.9013
AUC score: 0.9605072537847671

val Loss: 0.2610 Accuracy: 0.8921
AUC score: 0.9562095828725767

Used time: 20.768952612082163 min

Training complete in 416m
Best val Acc: 0.896816
```

Fine tune only the last linear layer

```
Epoch 19/19
current learning: 0.00037714951562499996
--------------------
train Loss: 0.4379 Accuracy: 0.8019
AUC score: 0.8535103063040204

val Loss: 0.4406 Accuracy: 0.8039
AUC score: 0.8565650138067603

Used time: 4.08056458234787 min

Training complete in 78m
Best val Acc: 0.807874
```

Other attempts to boost the performance:

1. **Fine tune different part of model, worse performance**
2. **Deeper Model, Resnet 34 Layer did not help with performance**

Other attempts to boost the performance:

1. Fine tune different part of model, worse performance

2. Deeper Model, Resnet 34 Layer did not help with performance

3. Use all the data without elimination →

No significant Difference between training and testing

```
Epoch 19/19
current learning: 0.00037714951562499996
--------------------
train Loss: 0.2423 Accuracy: 0.9013
AUC score: 0.9605072537847671

val Loss: 0.2610 Accuracy: 0.8921
AUC score: 0.9562095828725767

Used time: 20.768952612082163 min

Training complete in 416m
Best val Acc: 0.896816
```

```
Epoch 9/9
current learning: 0.000614125
--------------------
train Loss: 0.2500 Accuracy: 0.8972
AUC score: 0.9545222688026946

val Loss: 0.2672 Accuracy: 0.8902
AUC score: 0.9492408186033198

New best acc! Save model
Used time: 5.086348577340444 min
```

Other attempts to boost the performance:

1. Fine tune different part of model, worse performance
2. Deeper Model, Resnet 34 Layer did not help with performance
3. Use all the data without elimination →

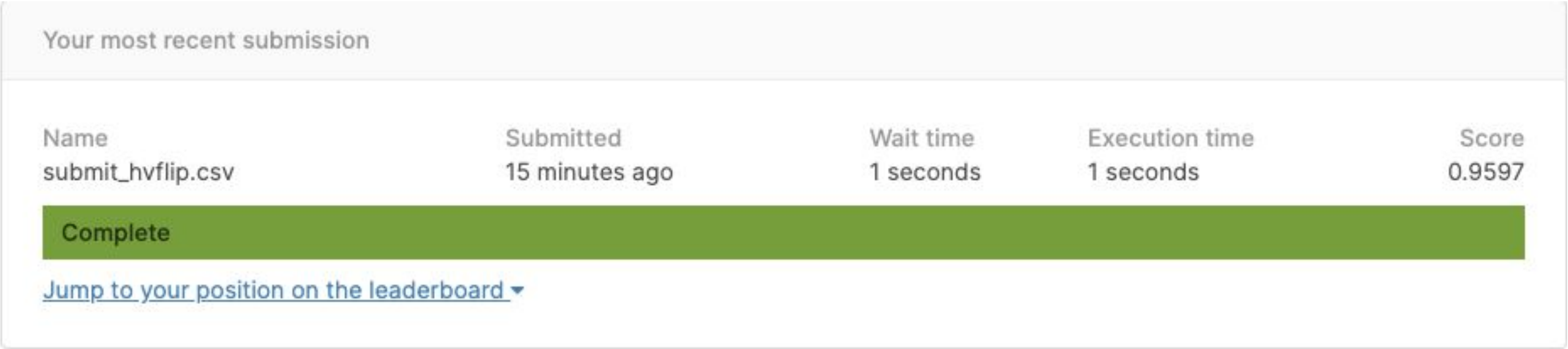
No significant Difference between training and testing

4. **How about using the whole image without cropping?**
   Big jump of performance AUC from 0.90 → 0.96
   Validation accuracy 0.95 → 0.99

   Possible reason: Although the label for testing dataset is only given to center 32 * 32 crop, there seems to be a strong correlation between tumor in the canter area and tumor in the whole picture.
   Therefore, a larger image gives more information during training, and results in better accuracy.

Conclusion

- Convolutional Neural Network is able extract useful information from images and it could be applied on histopathologic tissue scanning.
- Data preprocessing and augmentation help with the training process.
- The State-of-art CNN model, Resnet is able to achieve a 0.96 AUC testing score.



References

- First slide image source: https://wallpapercave.com/w/wp4708095
- All tissue images (PCAM) from: https://github.com/basveeling/pcam & https://www.kaggle.com/c/histopathologic-cancer-detection/data
- (https://www.kaggle.com/c/histopathologic-cancer-detection/data)
- B. S. Veeling, J. Linmans, J. Winkens, T. Cohen, M. Welling. "Rotation Equivariant CNNs for Digital Pathology". arXiv:1806.03962
- Ehteshami Bejnordi et al. Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer. JAMA: The Journal of the American Medical Association, 318(22), 2199–2210. Doi:jama.2017.14585
- He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.
- https://cs231n.github.io/convolutional-networks/
- Krizhevsky, A., Sutskever, I. and Hinton, G. E. "ImageNet Classification with Deep Convolutional Neural Networks"
- Medium blogpost: A Comprehensive Guide to Convolutional Neural Networks — the ELI5 wa
- https://www.programmersought.com/article/68543552068/
- He, Kaiming, et al. "Deep residual learning for image recognition."