LIVERPOOL HOPE UNIVERSITY
Est. 1844

MISS 2018
Medical Imaging Summer School

TISSUE CLASSIFICATION OF COLON CANCER HISTOLOGY IMAGES

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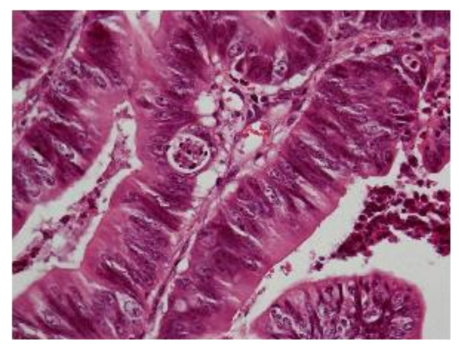
Abstract

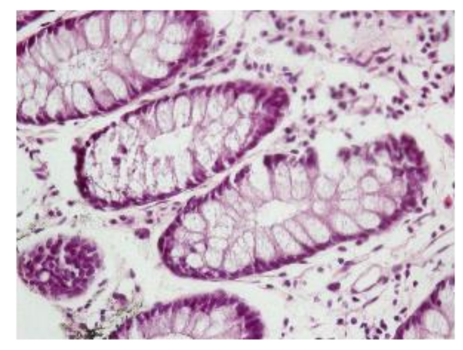
Colon cancer has a high death rate, but early diagnosis can prevent its progression. In this study, two approaches were used to classify hematoxylin and eosin stained images into normal, adenomatous polyp, and cancerous tissues. First, a shallow Convolutional Neural Network (CNN) is trained from scratch, whose architecture is designed to retrieve information at different scales. Google's Inception V3 architecture is then fine-tuned to do the classification. Fine-tuning outperformed learning from scratch.

Dataset

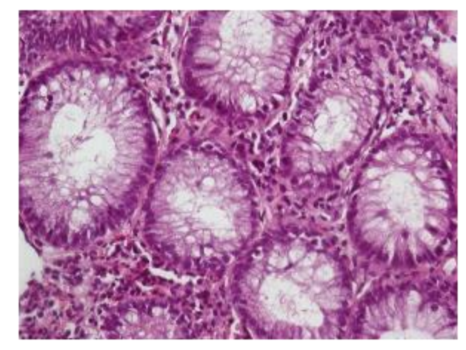
- 300 High resolution images (1200 x 1600 pixels)
- Magnification of 400x
- 100 cancerous images, 100 normal images and 100 polyp images.



Cancerous



Normal



Adenomatous polyp

Method 1 – CNN

Data Augmentation

- Image is divided in patches of 400 x 400 pixels.
- Each patch is rotated 0, 90, 180 and 270 degrees.
- Each patch is horizontally flipped.

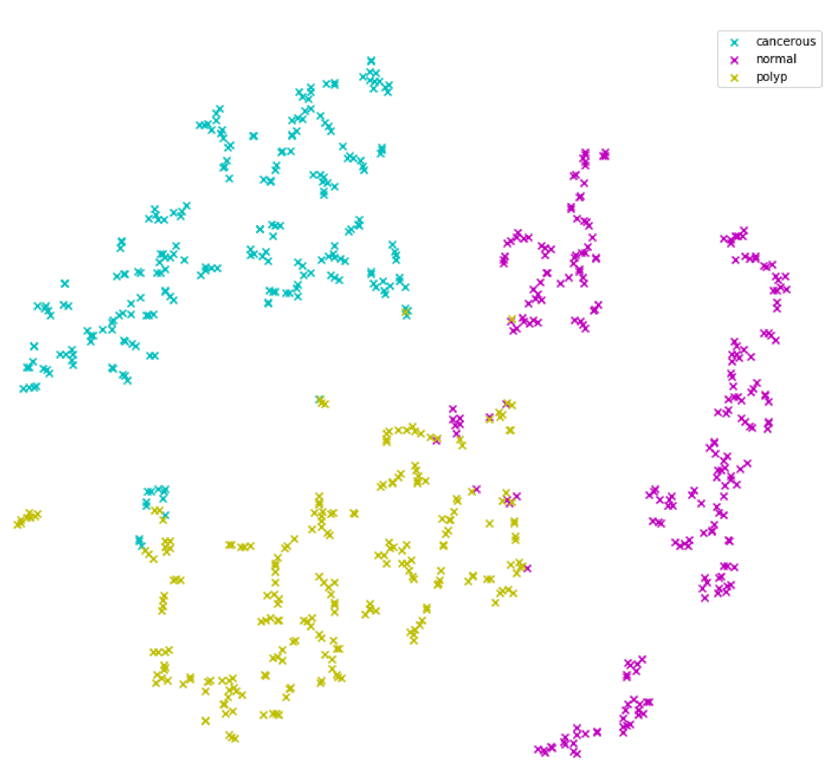
Architecture

The CNN architecture built for this task is inspired by a paper that classified breast cancer histology images using CNN [1, 2, 3]. The network is made of five convolutional-pooling layers, followed by three fully connected layers.

	Layer Type	Maps & Neurons	Kernel Size
0	Input	3M x 400 x 400N	
1	Convolutional	16M x 398 x 398N	3 x 3
2	Max-pooling	16M x 132 x 132N	3 x 3
3	Convolutional	32M x 130 x 130N	3 x 3
4	Max-pooling	32M x 65 x 65N	2 x 2
5	Convolutional	64M x 65 x 65 N	3 x 3
6	Max-pooling	64M x 32 x 32 N	2 x 2
7	Convolutional	64M x 32 x 32 N	3 x 3
8	Max-pooling	64M x 10 x 10 N	3 x 3
9	Convolutional	32M x 8 x 8 N	3 x 3
10	Max-pooling	32M x 2 x 2 N	3 x 3
11	Fully-Connected	256 N	
12	Fully-Connected	128 N	
13	Fully-Connected	3 N	

Training

The model is trained for 50 epochs and Adam optimisation is used with an initial learning rate of 0.001.



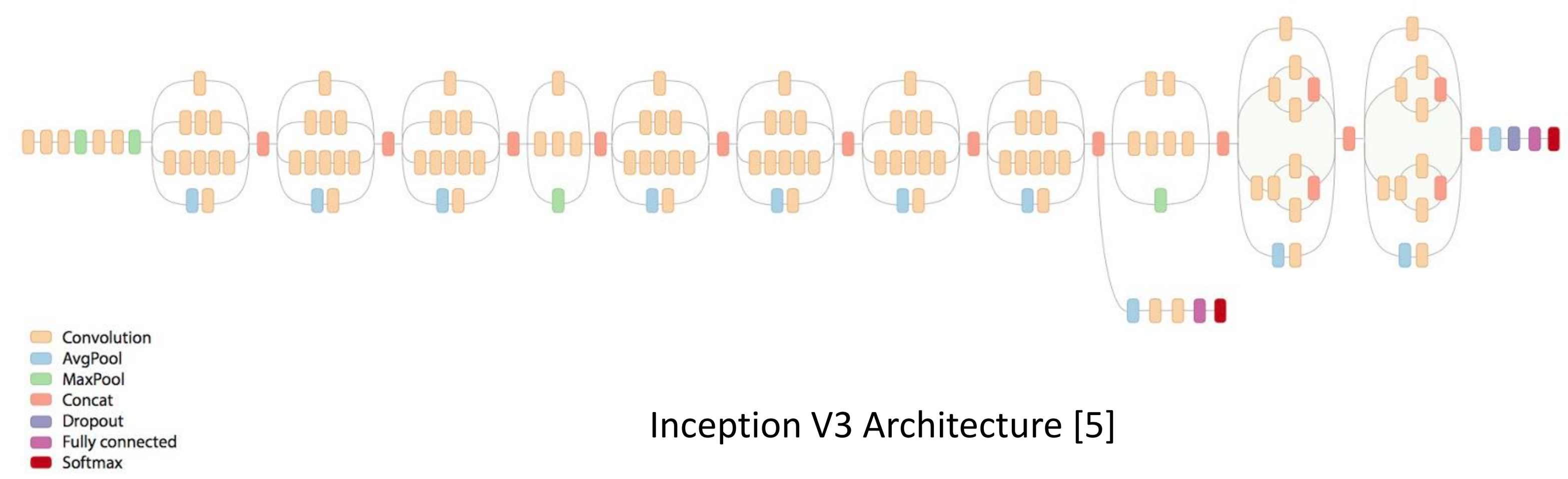
Two-dimensional representation of the training patches and their activations on the last hidden layer of the CNN using t-SNE [4].

Method 2 – Fine-tuning Google Inception V3

Data Augmentation

- Images are resized to 299 x 299 pixels
- Each image is rotated randomly between 0 and 359 and flipped vertically with a probability of 0.5.

Architecture



Inception V3 Architecture [5]

Training

All layers of the network are fine-tuned.

The model is trained for 30 epochs using the RMSProp optimization algorithm with a learning rate of 0.001.

Results and Discussion

For the first method, an image is classified by first classifying twelve 400 x 400 non-overlapping patches using patch-wise trained CNN model, then combining the result using majority voting to obtain image-wise classification. The overall image-wise classification accuracy for the test set was **91.21%**.

For the second method, the image classification accuracy for the test dataset was **93.33%**.

Using fine-tuning proved to be a successful mechanism to achieve a high accuracy from a small dataset, and learning from a pre-trained model requires less time than learning from scratch.

References

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[3] Alex Krizhevsky, Ilya Sutskever, and Geo_rey E Hinton. Imagenet classi_cation with deep convolutional neural networks. In Advances in neural information processing systems, pages 1097{1105, 2012.

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