**Investigation of Rotational Equivariance of Deep Neural Networks**

Submitted as part of Mini-project (EC64)

**BACHELOR OF ENGINEERING**
in
Electronics and Communication

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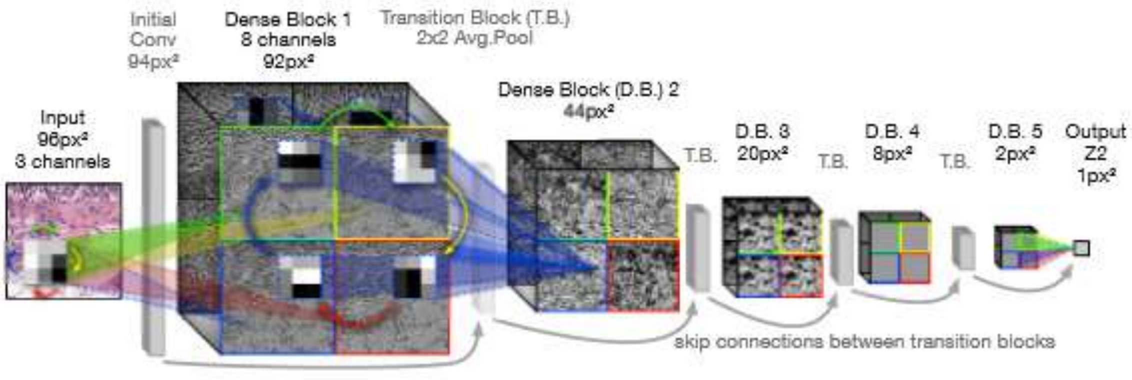
# Introduction
The amount of data generated by the image acquisition devices are huge and we are moving towards big data. Different types of data is available in the form of image, audio, video, MRI,CT scan, Neuroimaging Informatics Technology Initiative (Nifti), Minc, Digital Imaging and Communications in Medicine (Dicom) etc. Analysis and interpretation of this data efficiently is very crucial as it provides various information regarding the patient(disease).

Deep Learning is based on artificial neural networks, a layered and connected system of algorithms receiving and processing information. It is highly flexible and scalable, it can learn features by itself, making it an extremely powerful tool for image analysis increasing accuracy and speed. It also completes tasks consistently and enables new discoveries.

# Rotational equivariance of CNN’s
Convolutional layers used in a deep network are translation equivalent. If an input image is shifted in any direction and fed to the deep net it is equivalent to feeding the original non-shifted image to the deep net and then shifting the resulting feature maps. In other words, feature extraction is independent of spatial position. Today CNNs are the go-to solution for any task related to image processing, feature learning, etc. For many types of images, it is desirable to make feature extraction orientation independent as well. Typical examples are biomedical microscopy images or astronomical data which do not show a prevailing global orientation.Therefore it is a must that models designed for these data perform well even if there is a change in the orientation of the image given to the network.
Convolutional networks can be generalized to exploit larger groups of symmetries, including rotations and reflections. The possible way of achieving this is by using a new type of convolution layer called Group Convolution Layer instead of standard planar Convolution layer.
A Group Convolution Layer can be understood by comparing it with planar Convolution layer, in planar Convolution layer we translate the filter and compute the inner product similarly a Group Convolution Layer can be viewed as a process in which we transform/rotate the filter and then compute the inner product. This allows the network to learn feature maps associated with different rotated versions of the input image in a single pass.
The G-Convolutional layer can be implemented with the GrouPy , which is a python library that implements group equivariant convolutional neural networks in Chainer and TensorFlow and supports other numerical computations involving transformation groups.

# Benefits of Group Convolution Layer

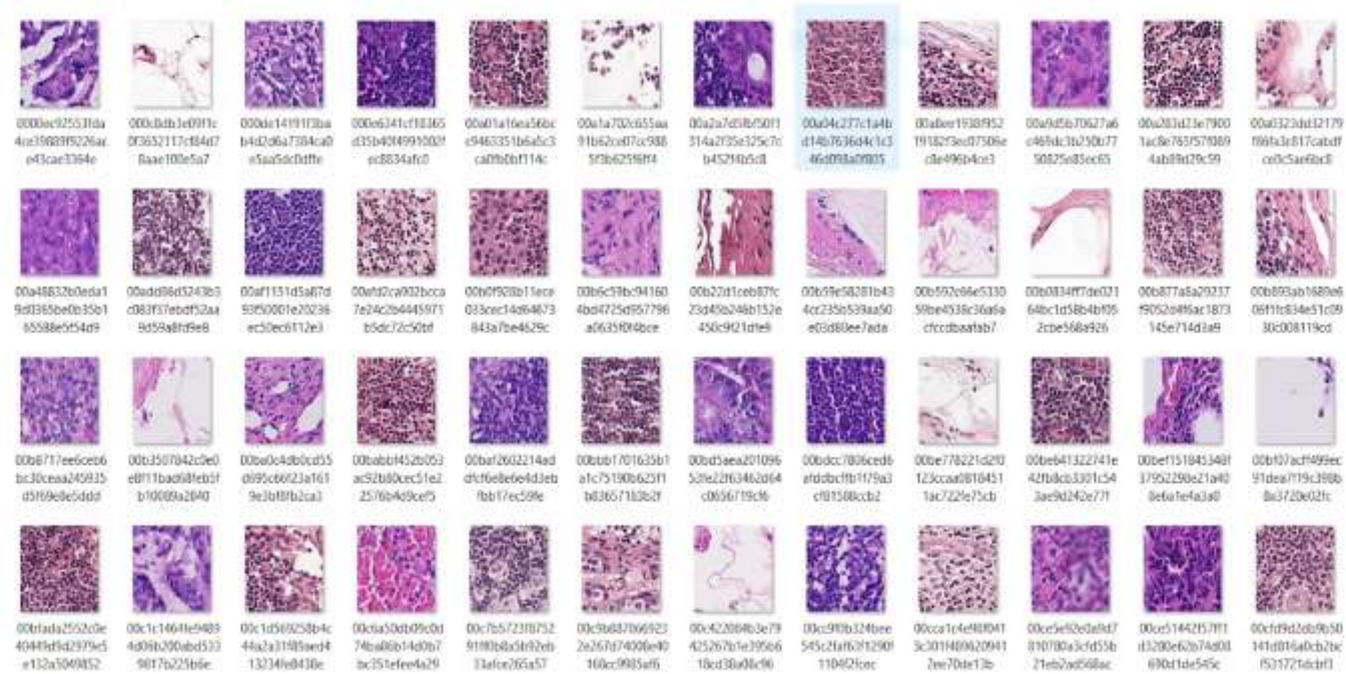
- Can simply be used by replacing standard convolution layer in a deep network.
- Fast learning process
- Allows the network to learn feature maps associated with different rotated versions of the input image in a single pass
- Negligible computation overhead
- Improves accuracy

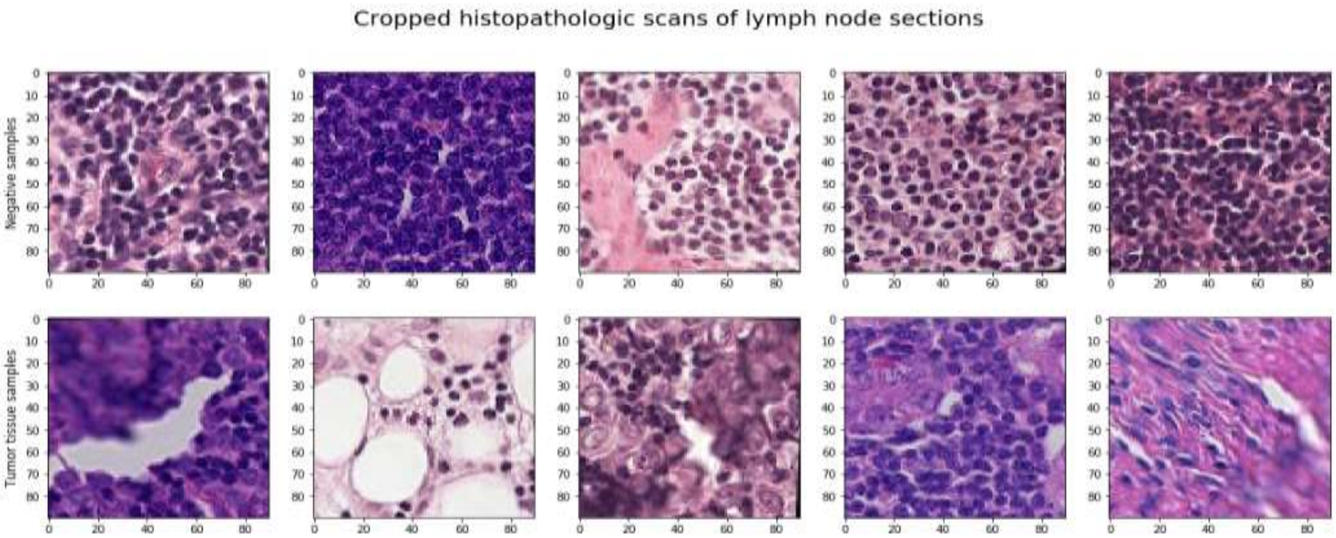


# DataSet description: Identify metastatic tissue in histopathologic scans of lymph node sections

This dataset provides with a large number of small pathology images to classify. Files are named with an image id. The train_labels.csv file provides the ground truth for the images in the train folder. You are predicting the labels for the images in the test folder. A positive label indicates that the centre 32x32px region of a patch contains at least one pixel of tumor tissue. Tumor tissue in the outer region of the patch does not influence the label. This outer region is provided to enable fully-convolutional models that do not use zero-padding, to ensure consistent behaviour when applied to a whole-slide image.

The original PCam dataset contains duplicate images due to its probabilistic sampling, however, the version presented on Kaggle does not contain duplicates. We have otherwise maintained the same data and splits as the PCam benchmark.
https://www.kaggle.com/c/histopathologic-cancer-detection/





## Reference

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[2] Cohen, T.S., et al.: Group equivariant convolutional networks. (2016)