



UPPSALA
UNIVERSITET

Peipei Han
Rebecca Stenberg

Project in
Computational
Science
January 2020

Supervisors:
Joakim Lindblad
Nataša Sladoje

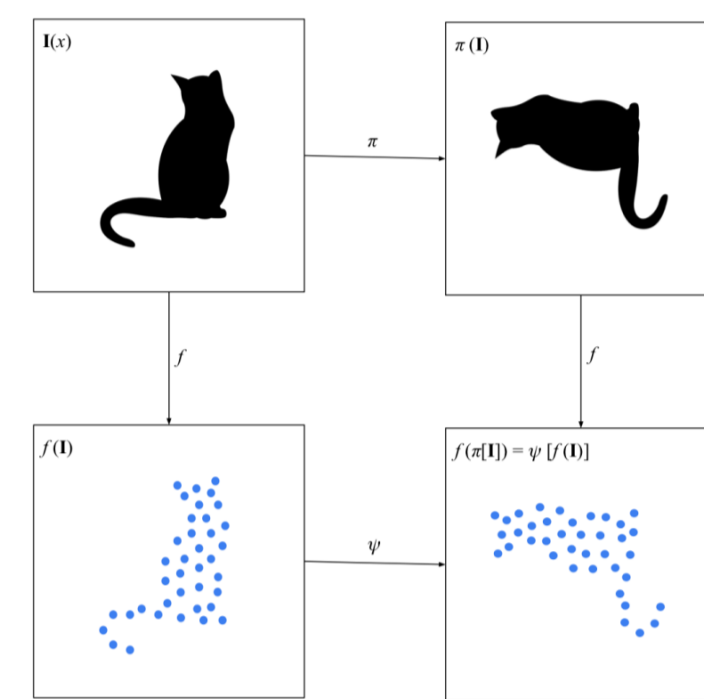
Department of
Information
Technology

Image Classification using Rotation Equivariant and Invariant CNNs

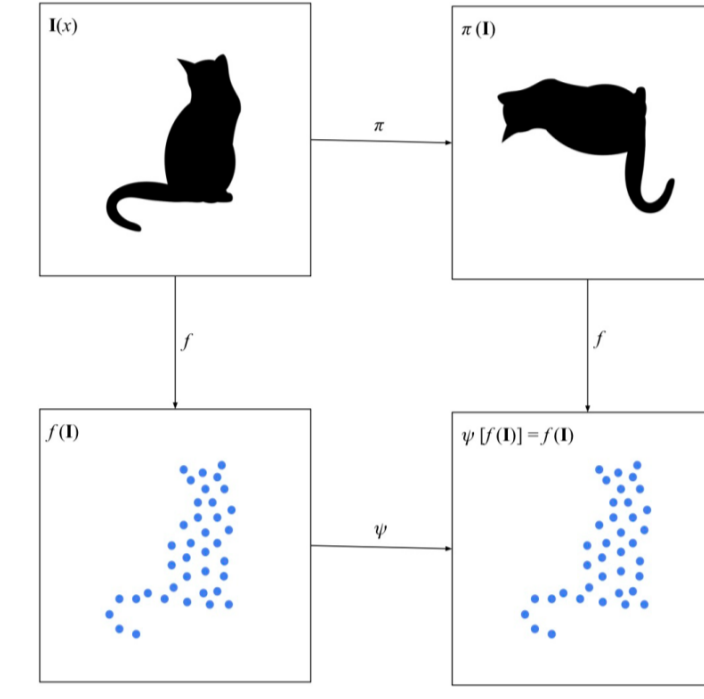
Project Goal

Evaluate three rotation equivariant and/or invariant CNN models on two datasets using a standard CNN as a baseline

- Group Equivariant CNN (G-CNN) [1]
- Conic Convolution and DFT network (CFNet) [2]
- Harmonic Networks (H-Nets) [3]



Rotation Equivariance: A transformation in the input will give a proportional change in the output.

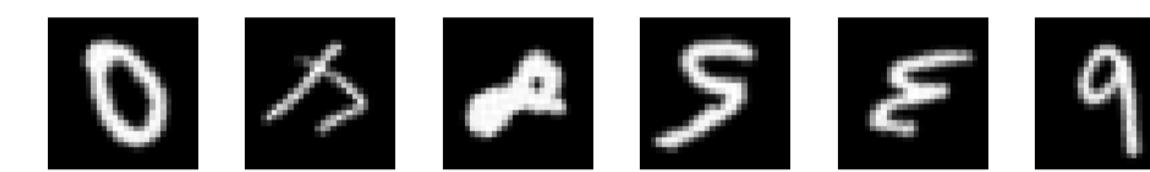


Rotation Invariance: A transformation in the input does not change the output.

Data

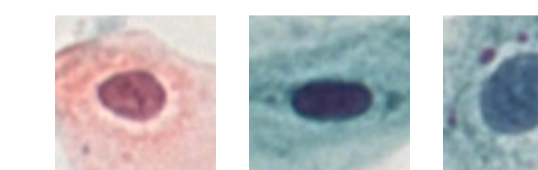
Rotated MNIST

- Handwritten digits rotated with uniformly generated angles between 0 and 2π
- 12'000 training images, 50'000 test images
- Size 28x28x1

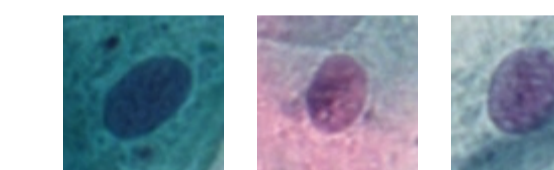


Oral cells

- Bright-field microscopy slides segmented into nearly 130'000 images of cells
- Size 80x80x3



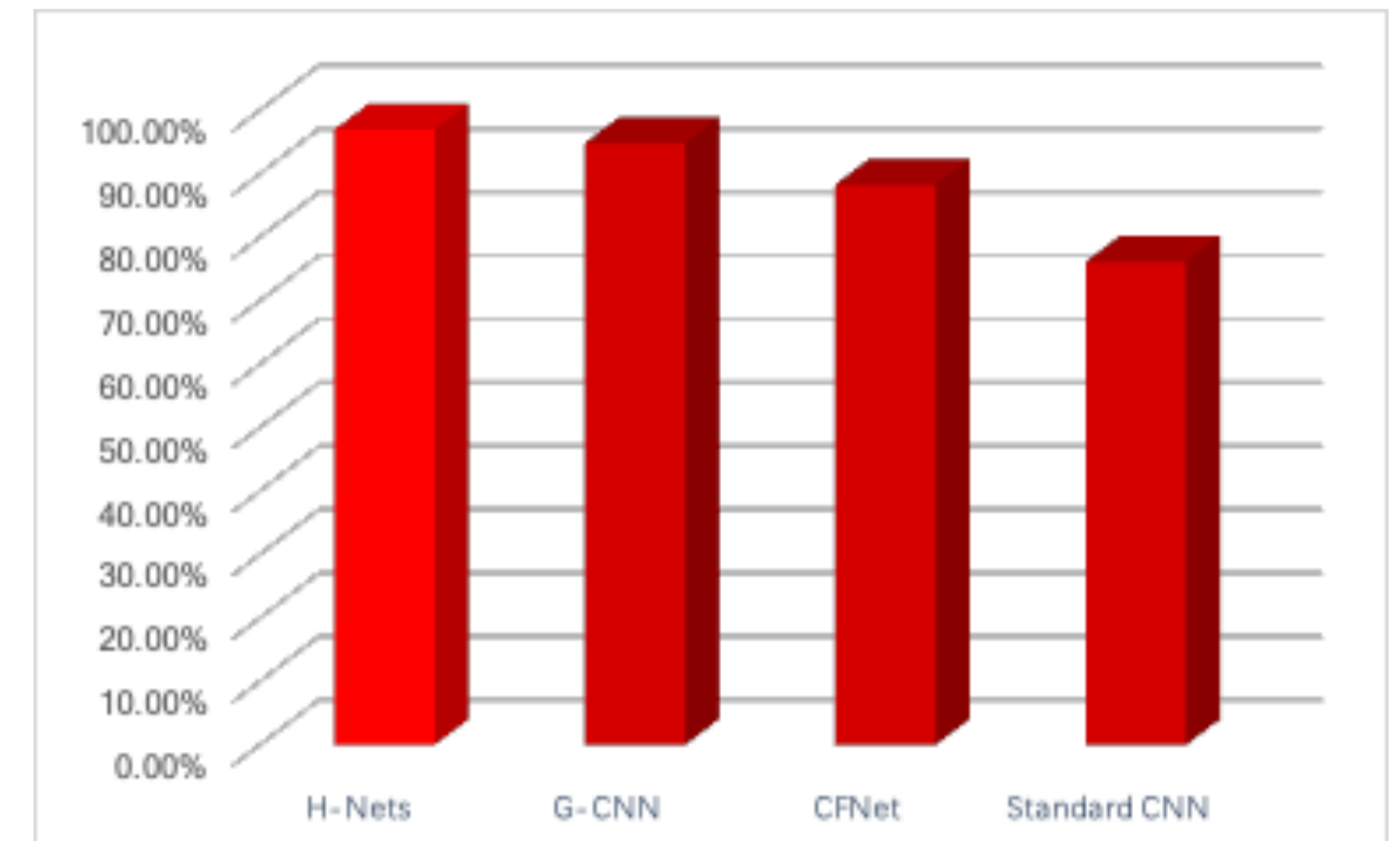
Cancerous cells



Healthy cells

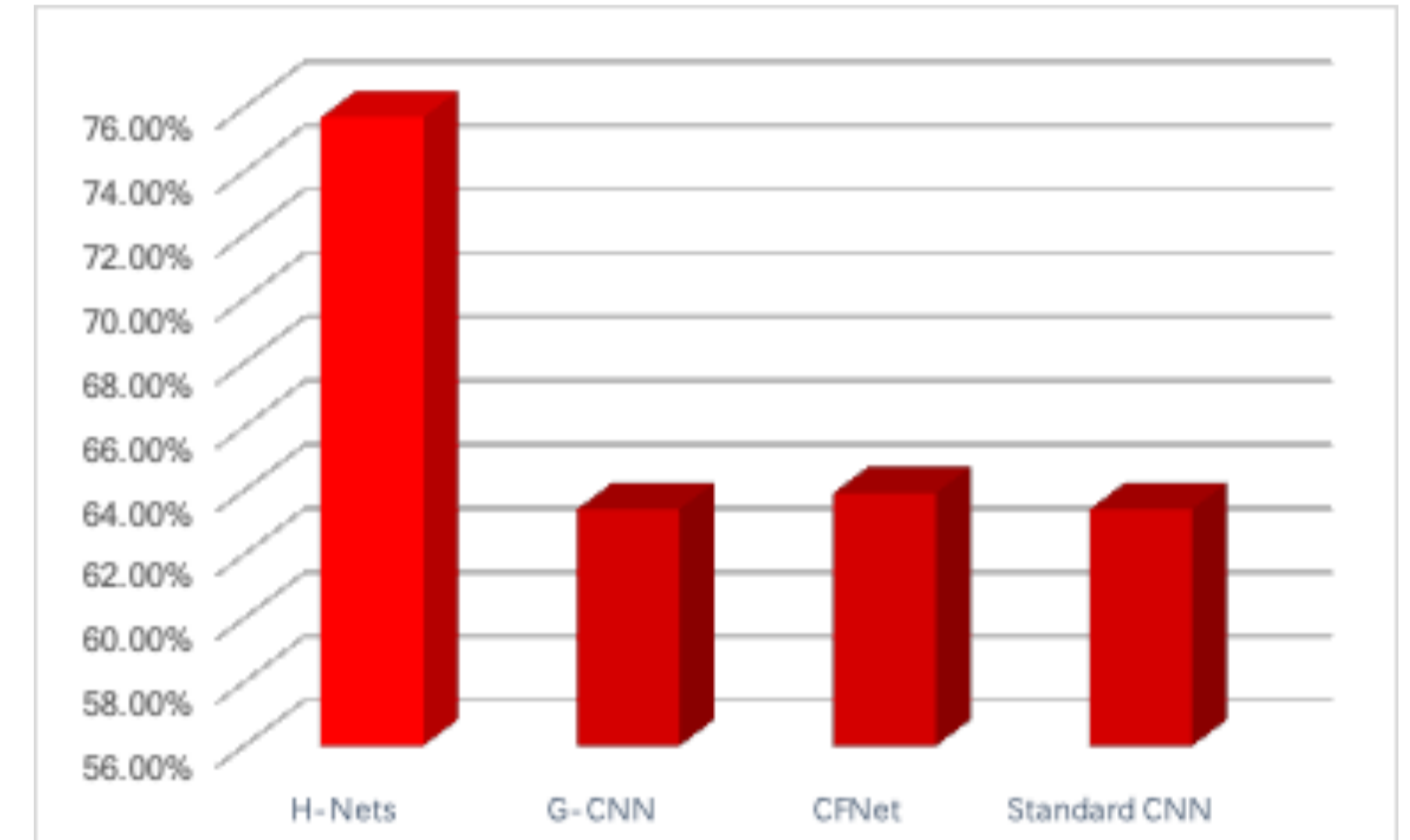
Results

Rotated MNIST Accuracy



Model	Accuracy	Epochs
H-Nets	96.98%	50
G-CNN	94.86%	50
CFNet	88.34%	50
Standard CNN	76.19%	50

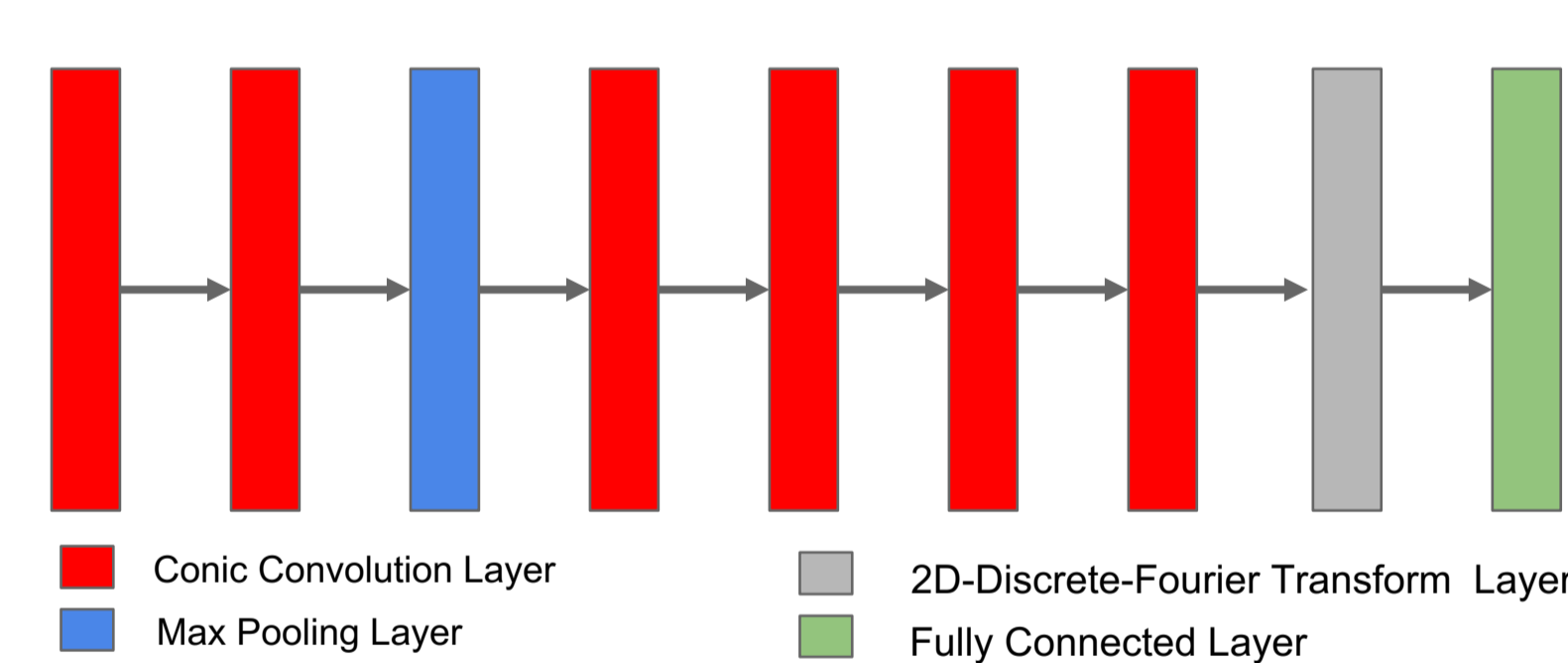
Oral Cancer Accuracy



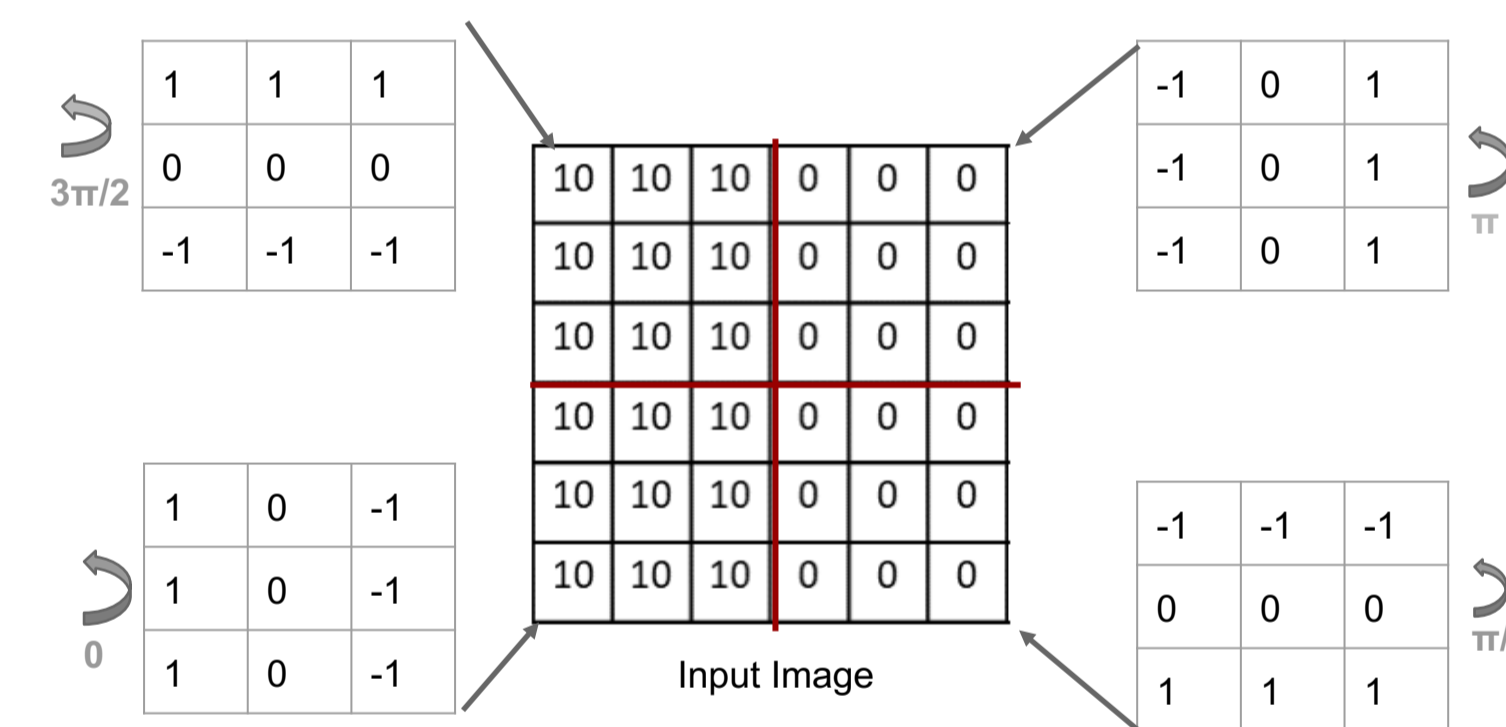
Model	Accuracy	Epochs
H-Nets	75.70%	10
G-CNN	63.42%	10
CFNet	63.93%	10
Standard CNN	63.42%	10

H-Nets outperforms G-CNN, CFNet and standard CNN in both MNIST and oral cancer dataset with higher accuracy.

CFNet

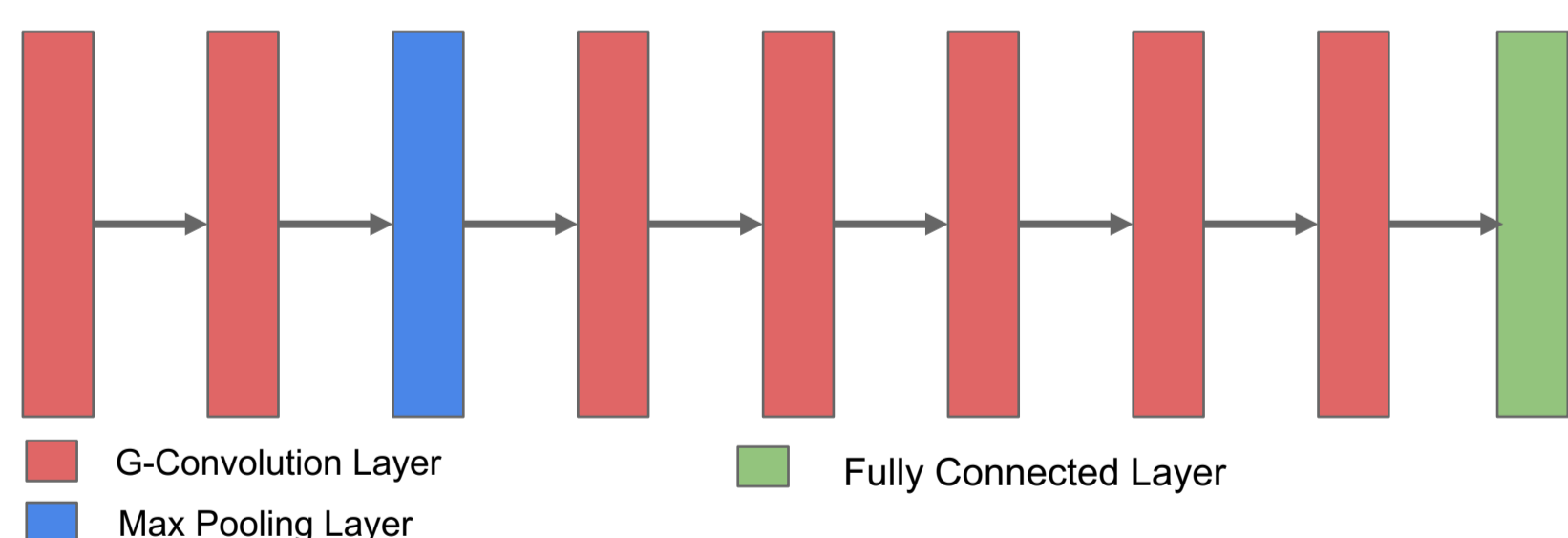


Conic Convolution Layer

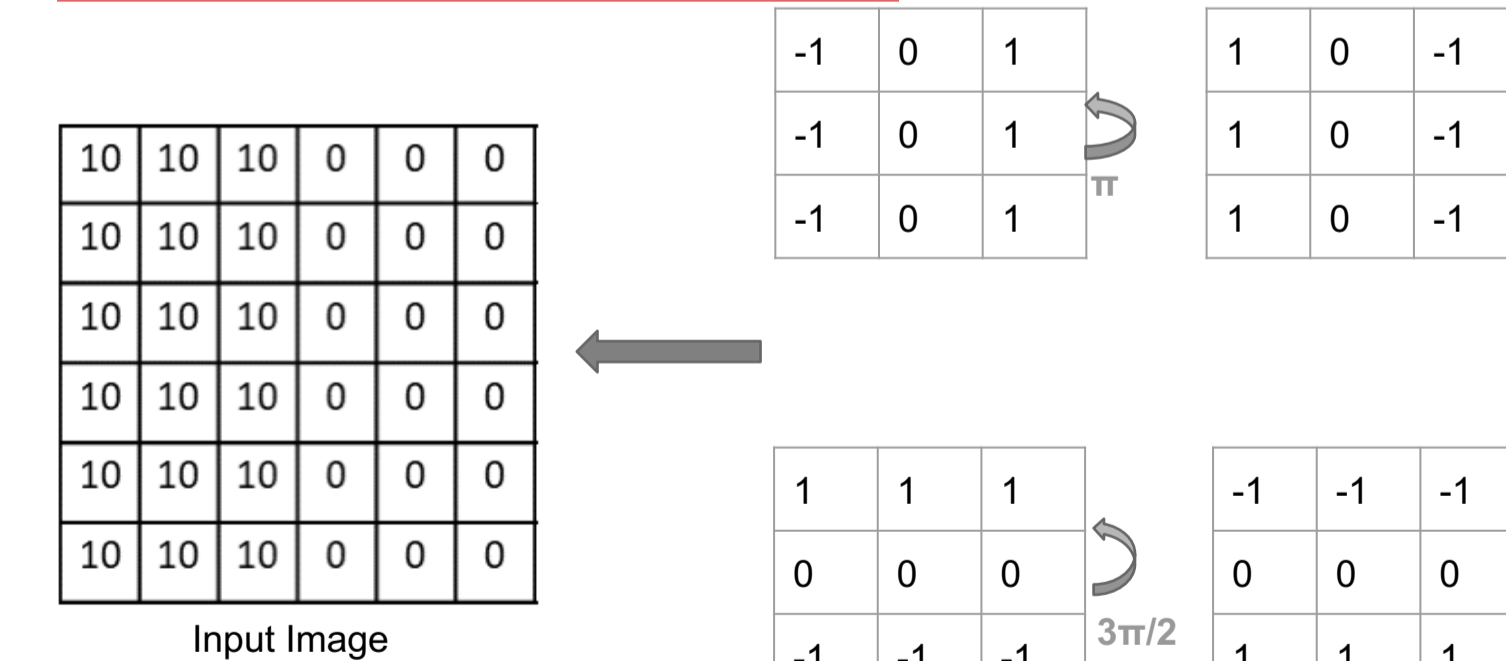


- CFNet splits the input feature map into conic regions which are convolved with rotated filters.
- It integrates 2D-DFT layers for encoding global rotational invariance.

G-CNN

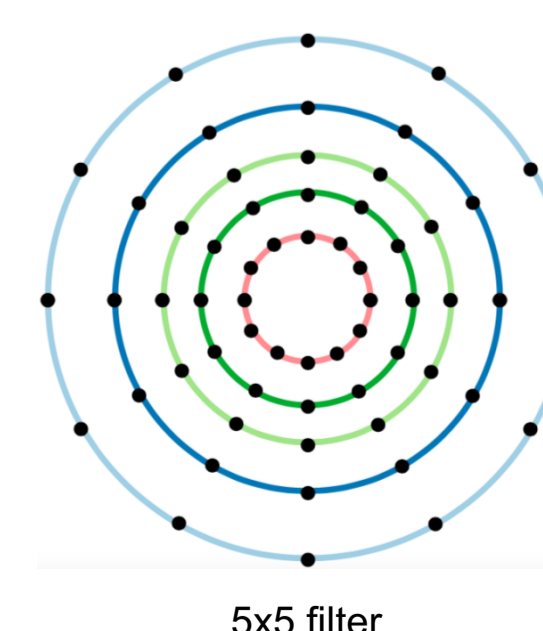
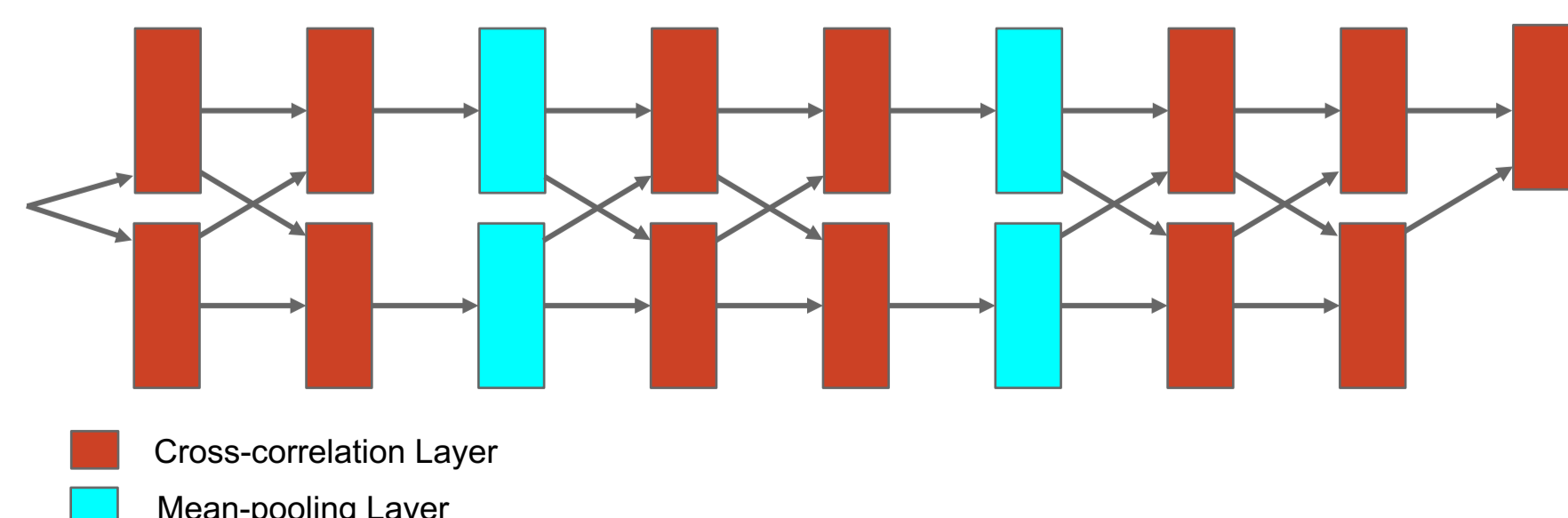


G-Convolution Layer



- G-CNN replaces the correlation shifting with a group of function which consists of rotations of 90° and translations.
- The transformations are applied to filters instead of input feature map which is more efficient.

H-Nets



- H-Nets hard-bakes 360° rotation equivariance into the structure by using filters from the circular harmonics family.
- Each filter picks up a different angular frequency in the input which is processed in a separate stream.
- In the polar representation of the filter each radius has a single learnable weight and the whole filter has a bias.

[1] Taco S. Cohen & Max Welling. Group Equivariant Convolutional Networks 2016-06-03
 [2] Benjamin Chidester1, Tianming Zhou1, Minh N. Do2 and Jian Ma1. Rotation equivariant and invariant neural networks for microscopy image analysis 2019
 [3] Daniel E. Worrall, Stephan J. Garbin, Daniyar Turmukhambetov & Gabriel J. Brostow. Harmonic Networks: Deep Translation and Rotation Equivariance. 2017-04-11.