

We propose a pipeline to unsupervisedly learn Rotation-invariant Representations for the classification of haematopoietic cells from bone marrow microscopy images.

## **Motivation**

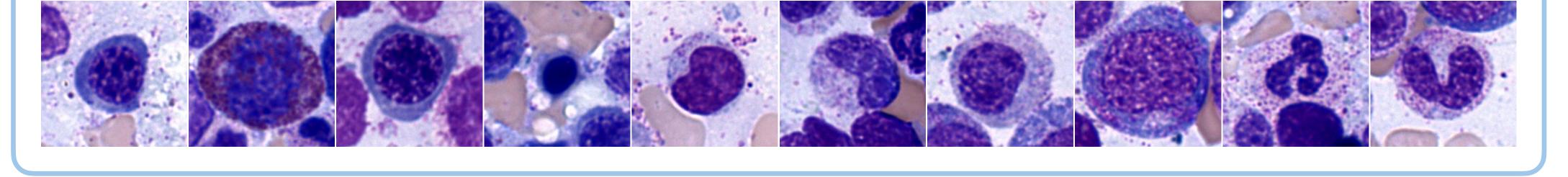
Analysis of the blood cell distribution in bone marrow is necessary for a detailed diagnosis of many haematopoietic diseases, such as leukaemia. While this task is performed manually on microscope images in clinical routine, automating it could improve reliability and objectivity.

As with many medical image analysis tasks, annotation shortage is a limiting factor. With unand semi-supervised learning techniques, this can be mitigated. We try to exploit the arbitrary orientation of cells to perform regularisation by enforcing rotation invariant representations.

# Reconstructed Images Baseline HNet (r=2) HNet (r=0)

## Data

Images are obtained from Pappenheim-stained human bone marrow samples using 63x magnification. From these, patches of size 256 x 256 px<sup>2</sup> centred around individual cells are extracted. Around 11k cells are of unknown cell type (used for unsupervised training) and 6k cells are of known cell type (used for supervised evaluation). Examples are shown below.



## **Methods**

## **Spacial Transformer Network (STN)**

Predict (only) rotation (w.r.t. arbitrary angle)

Normalise w.r.t. rotation

Run Auto-encoder on normalised image

Re-rotate image (angle through side-channel)

## **Harmonics Network (HNet)**

Use spherical harmonics in convolution kernels

We use these filters in ResNet-like network

**r=0** filters are rotation invariant

**r=2** filters are rotation equivariant

# Results Enforcing rotation invariance often yields symmetric reconstructions. Classification results do not improve in purely unsupervised case. Harmonics Equivariance Only STN Harmonics Invariant 0.6 0.4 0.2 0.28 0.57 0.4 0.52 HNet (r=2)0.29 HNet (r=0)0.5 0.61 0.2 0.3 0.1 0.5 0.6 F1-Score





