

# ML update - 25<sup>th</sup> Oct



**MoEDAL**

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# Previously....

- CNN on 3D images, didnt do well.
- Unstable learning

- Cropping cutting of full structure of objects

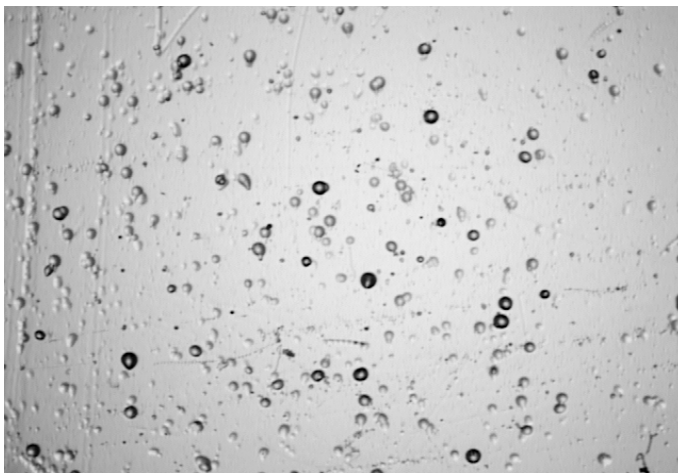
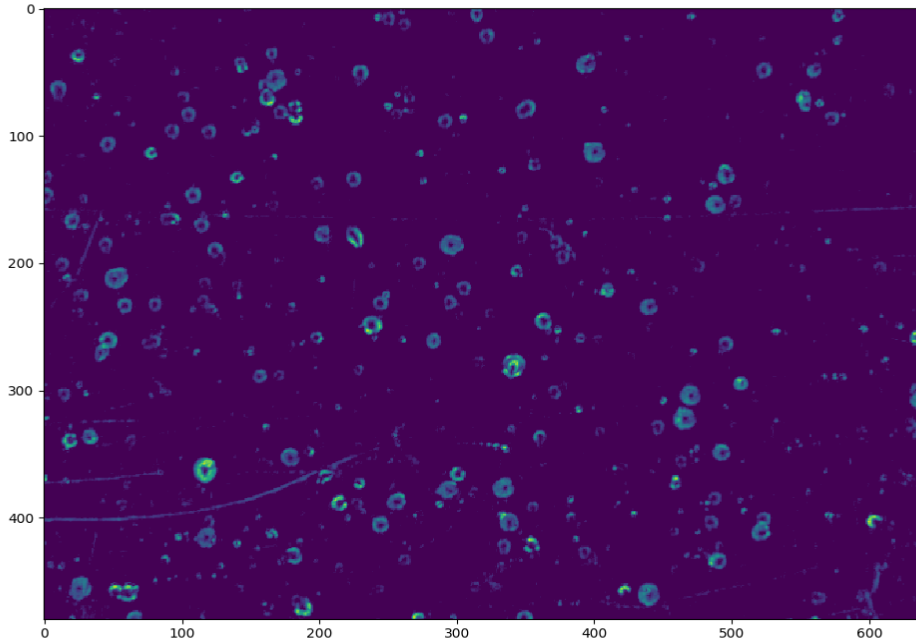
- Poor statistics for candidates vs bkg

- Noisy images

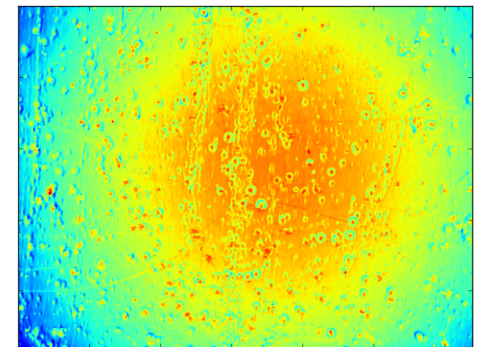
# Image Clean-up

## Clean up / denoise techniques

- Redefining zero relative to Image Average.
- Thresholding – remove shallow background features
- Techniques for filtering out small objects (currently using binary opening/closing, more work todo)
  - since we know pit size ~ ionisation

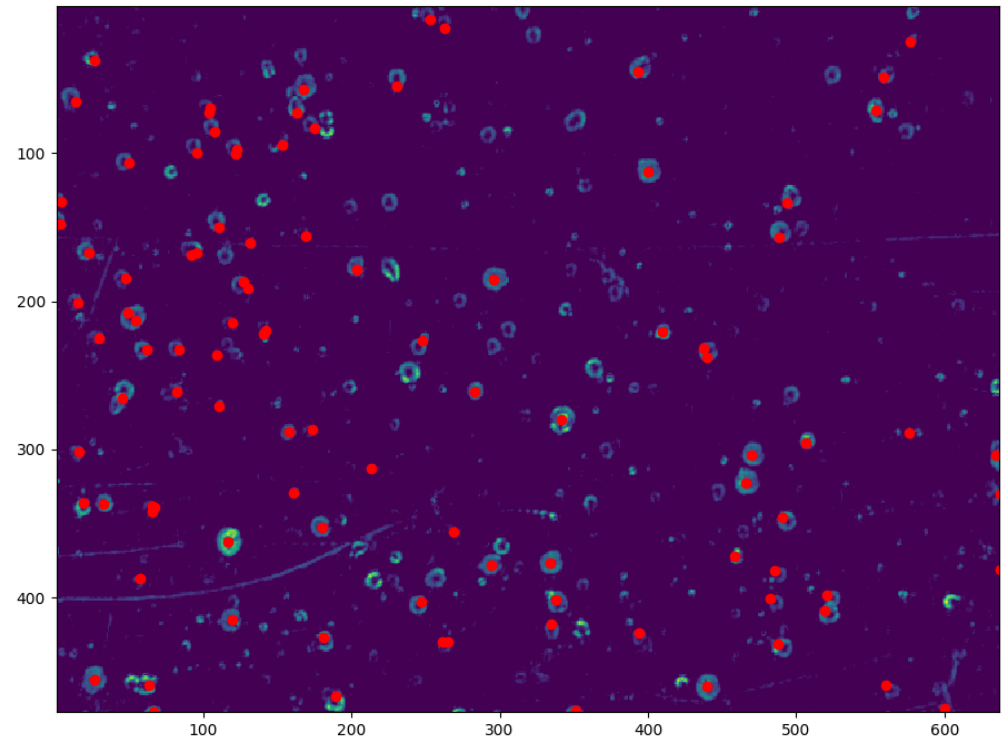


Eg, averaging two slides in different positions highlights central illumination bias



# Position labelling

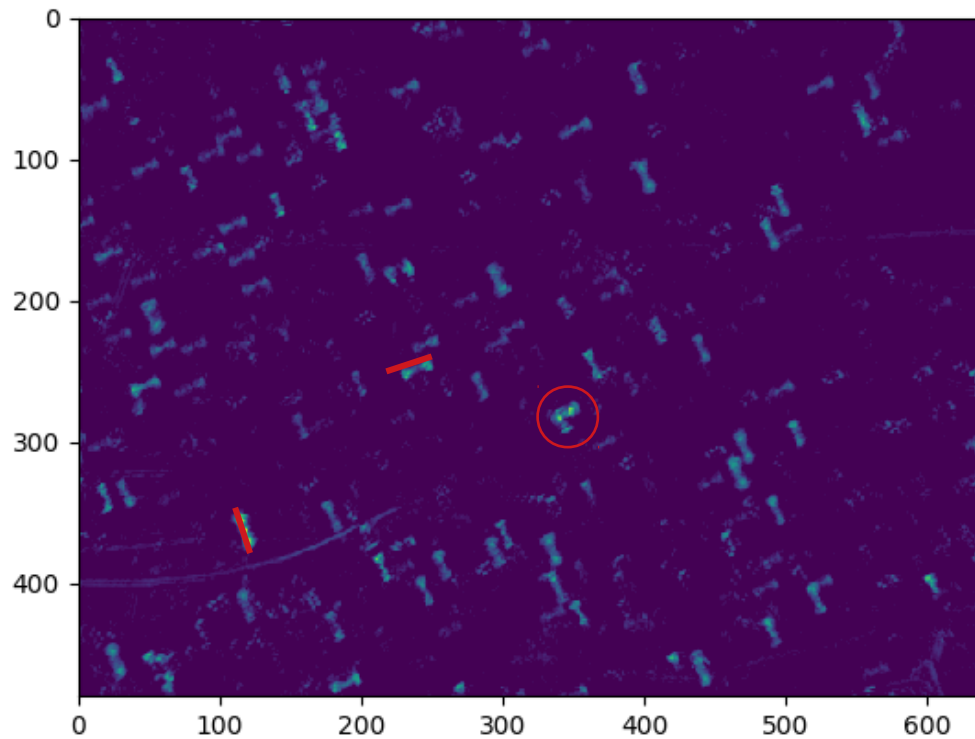
- Decouple position and classification
- Localisation based on image segmentation from classical image processing
- Choice of masks to use. Combining with backlit / halo images improves noise discrimination



Spent time trying to perfect pit localisation accuracy. However pit localisation doesn't have to be perfect! Just has to pre-select training examples for CNN

# Phase Information

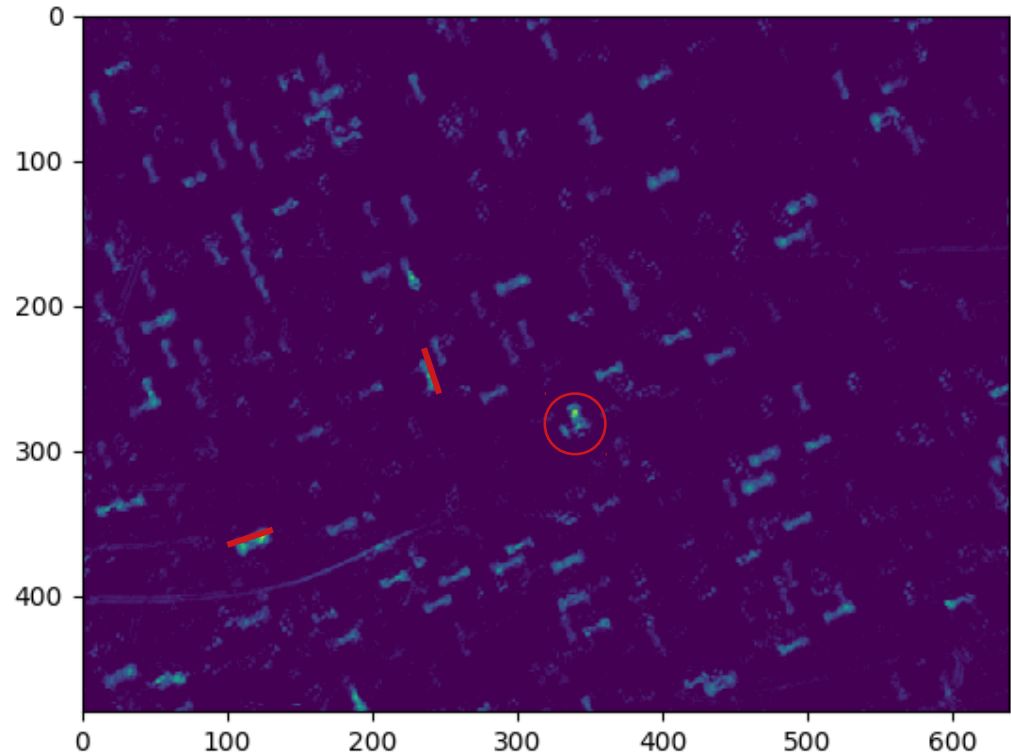
## In Phase



Illumination angle determines if pits are on top or bottom surface

Filtered/  
transformed and  
projected into 2d  
Dilute what desnt  
match pattern

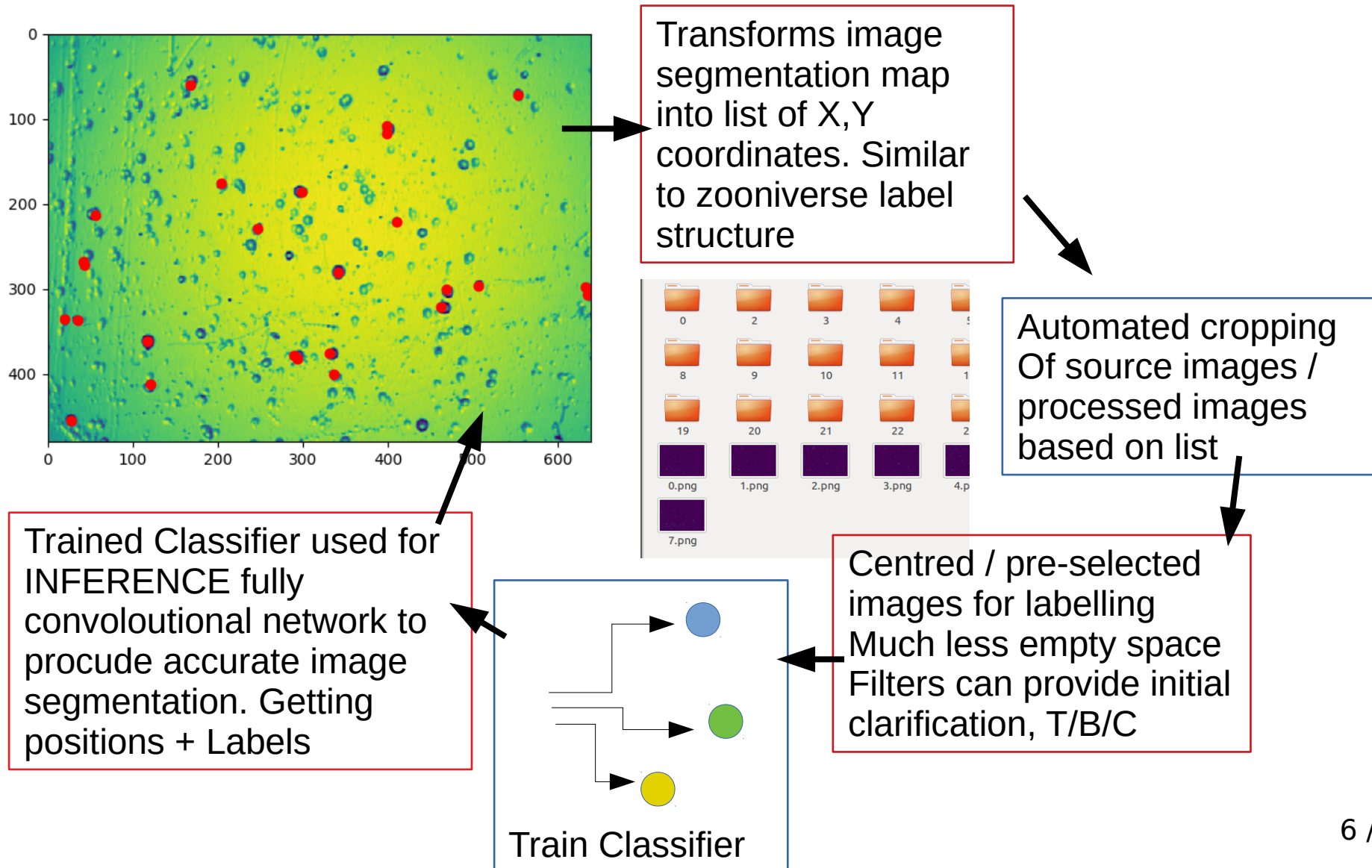
## In Anti-Phase



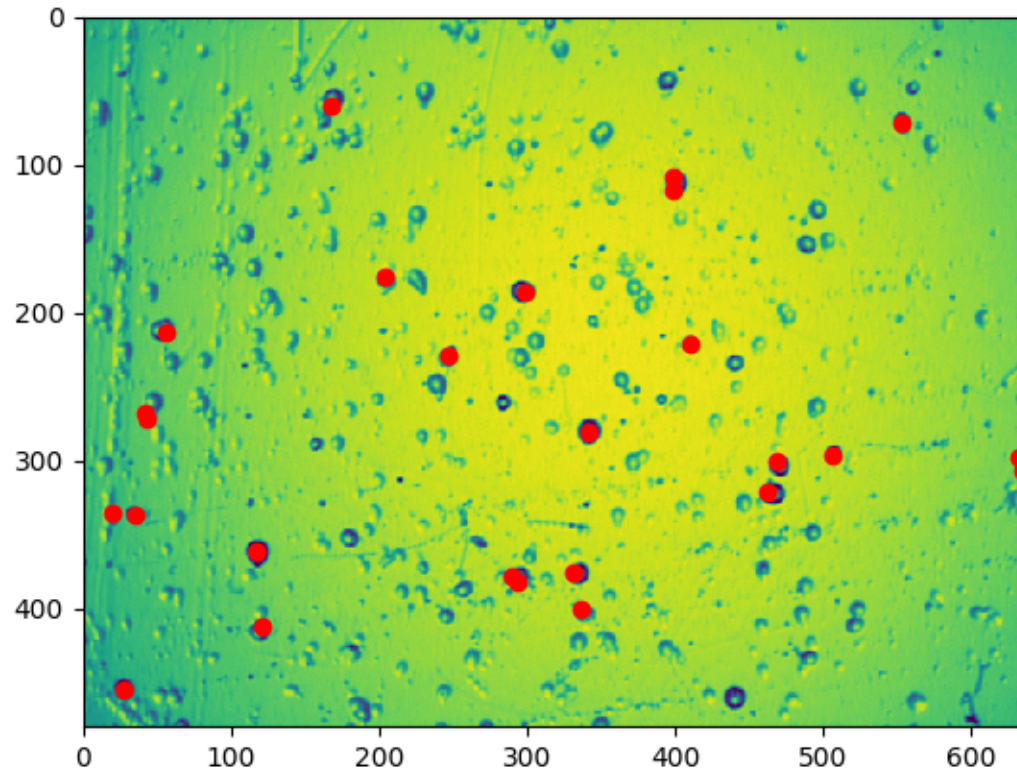
Candidate holes  
show features of  
both.

Many Many examples of  
top surface and bottom  
surface pits. Possible to  
train feature learning on  
these.

# Position labelling



# Scales easily

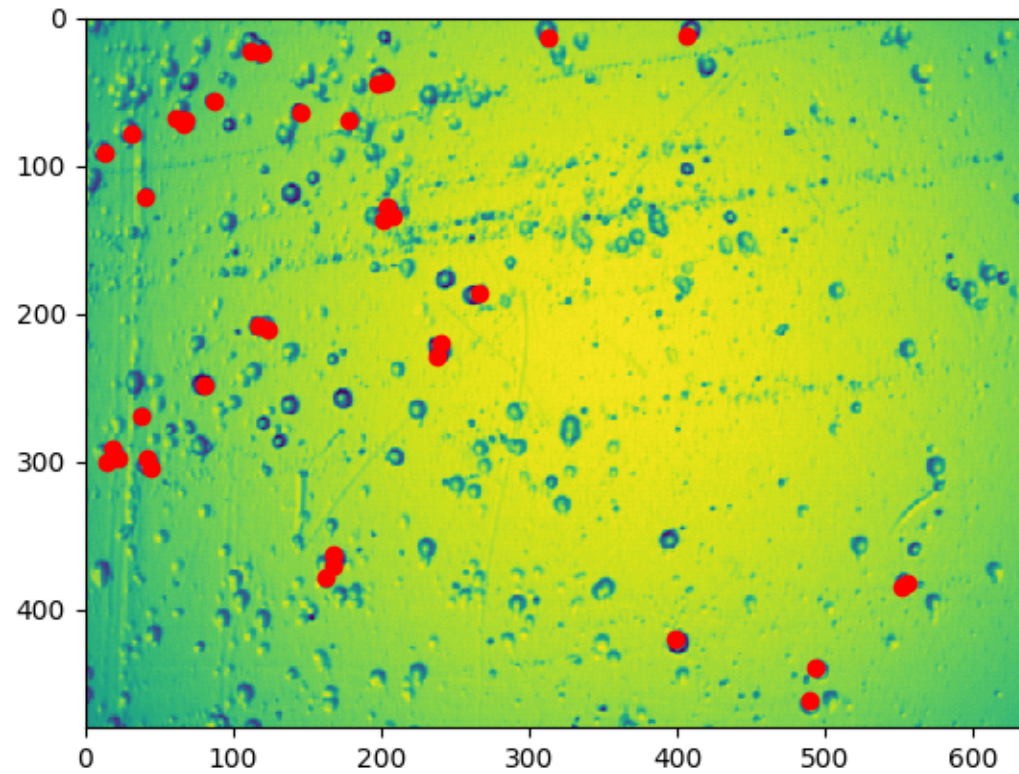


Green colour reflects heatmap of numpy-image-array

X,Y coords derived from

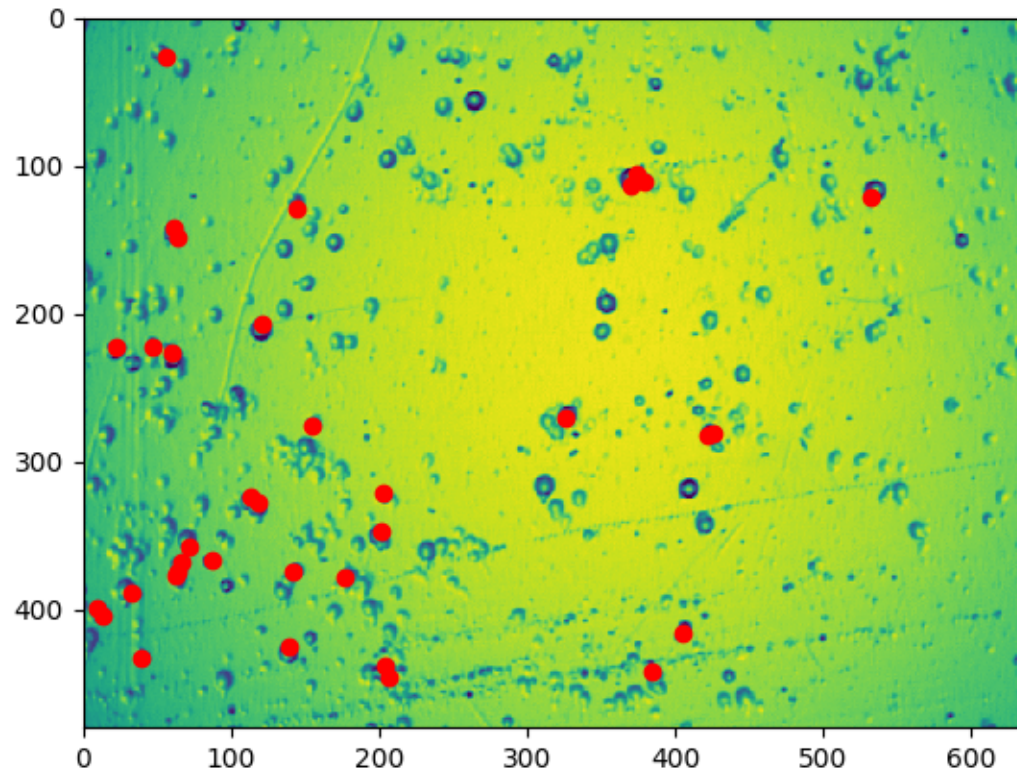
# or fraction of Pits selected depends on threshold values, and no. filters required

# Scales easily

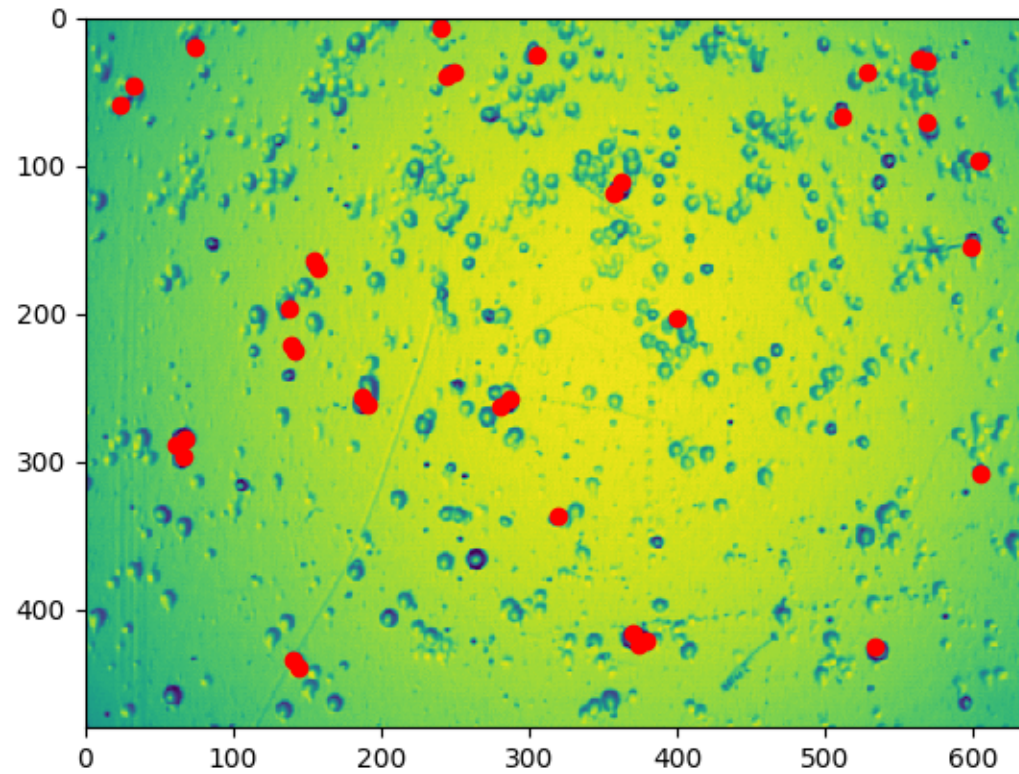




# Scales easily



# Scales easily



# Scales easily

