Machine Learning For Etch-Pit Identification for MoEDAL

MoEDAL

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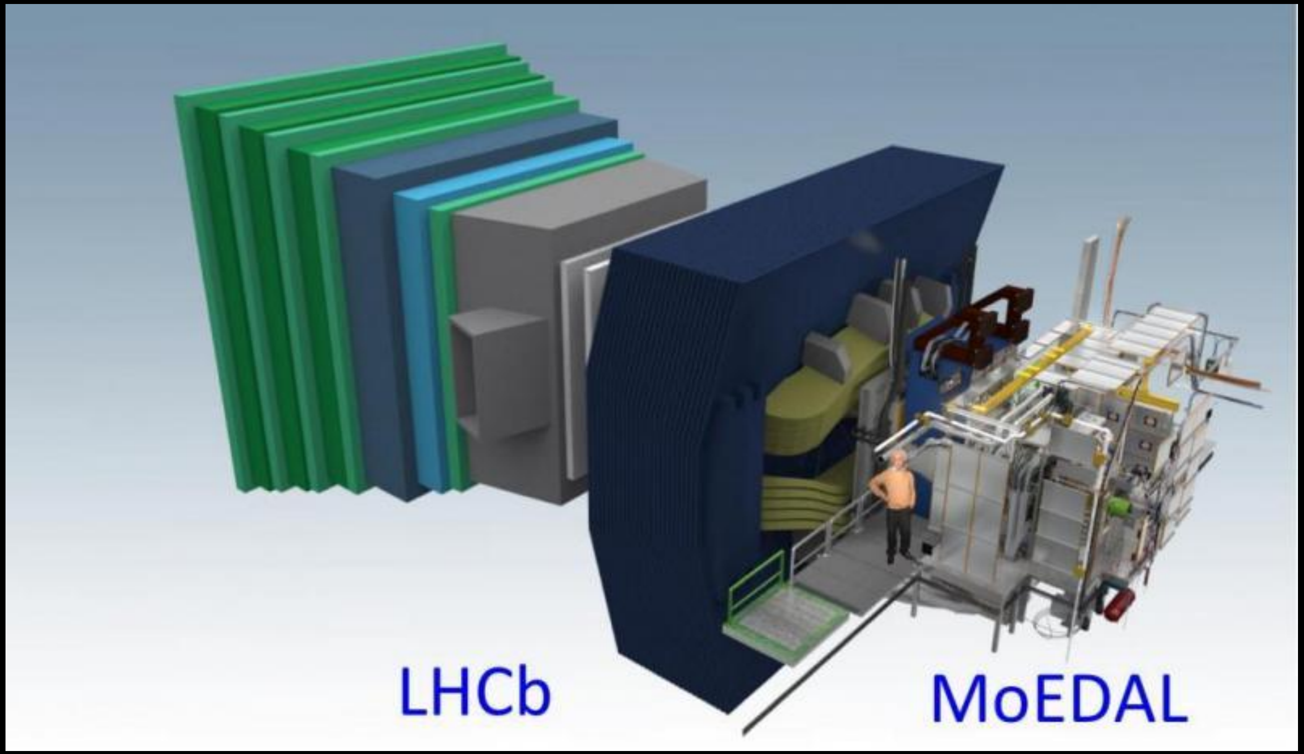
Queen Mary
University of London

MoEDAL

MoEDAL = The Monopole & Exotics Detector at the LHC



Search for highly ionizing particles such as magnetic monopoles and other exotic avatars of new physics

Nuclear track detectors and aluminium trapping detectors

Nuclear Track Detectors

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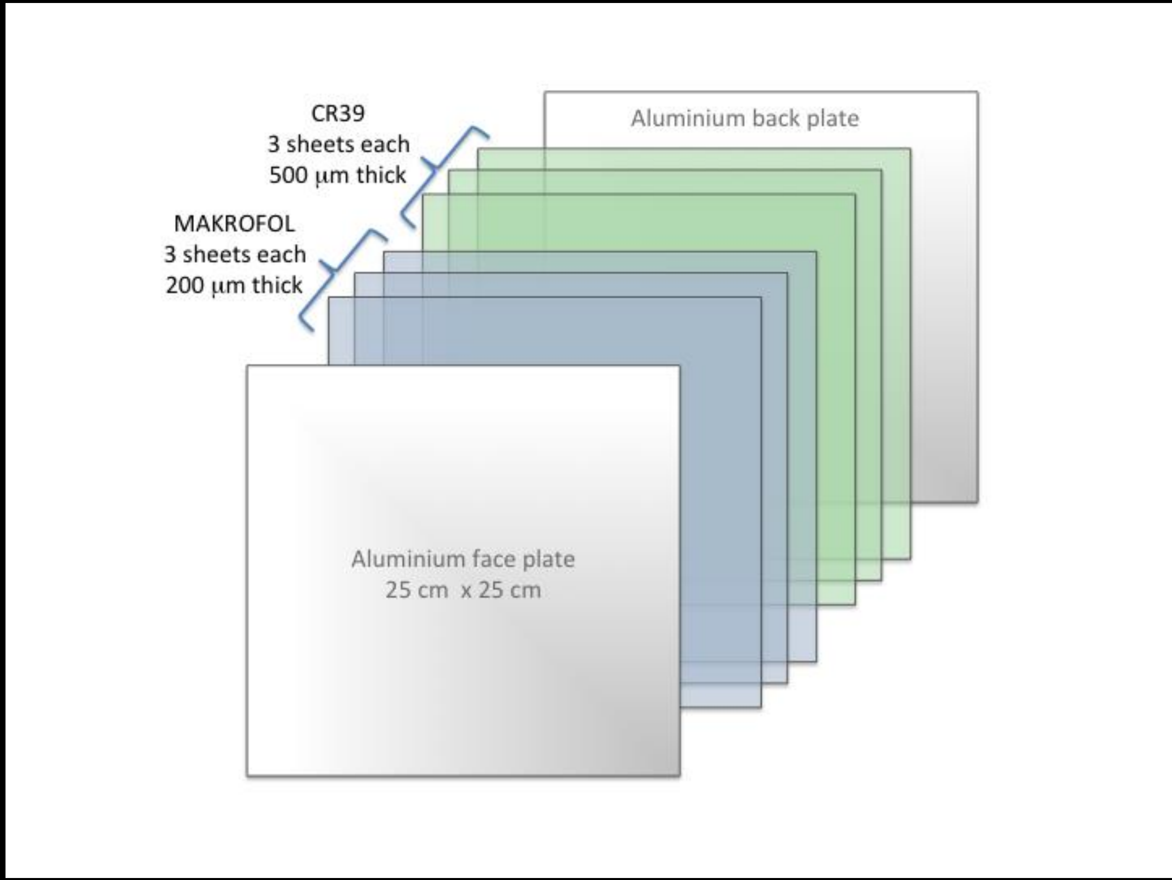

Search for highly ionizing particles such as magnetic monopoles and other exotic avatars of new physics

Highly ionising particles passing through the NTD cause microscopic damage to the polymer that can be reveal with etching

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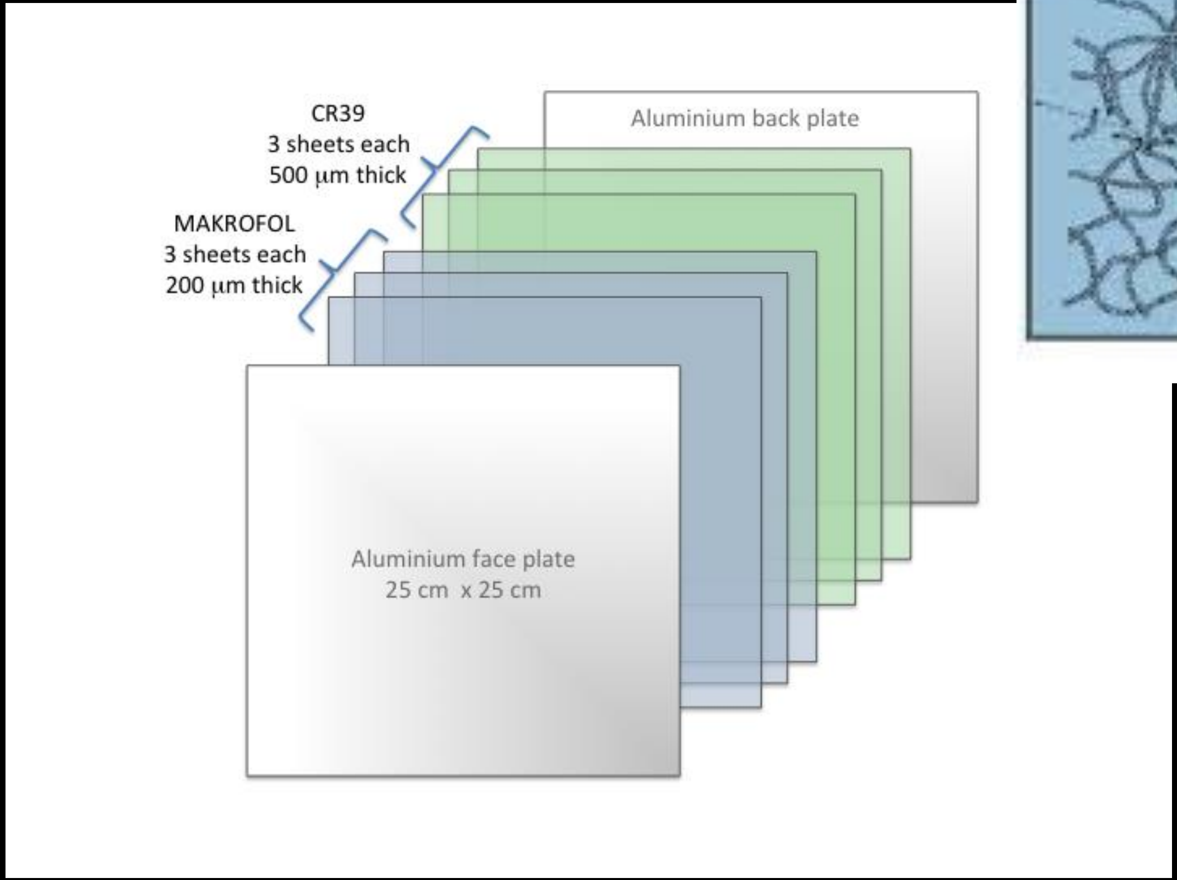

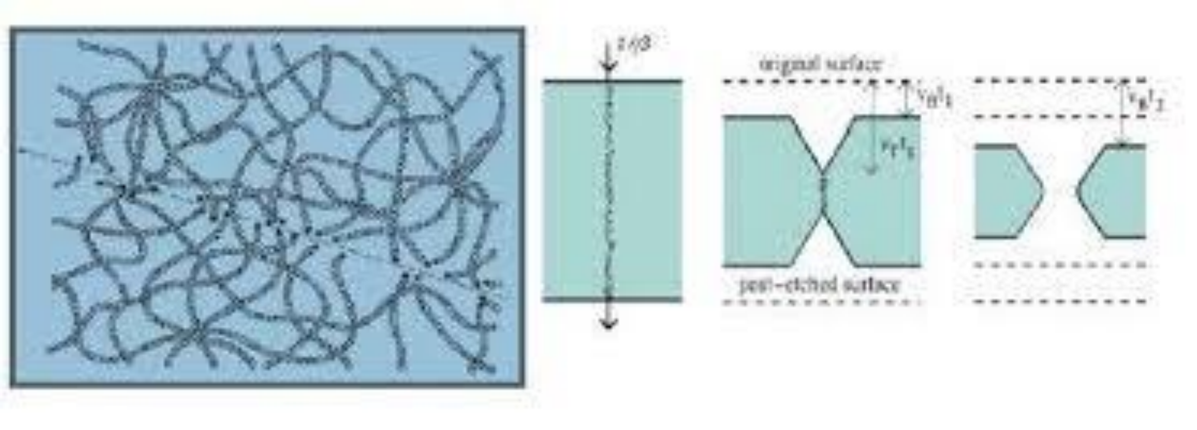

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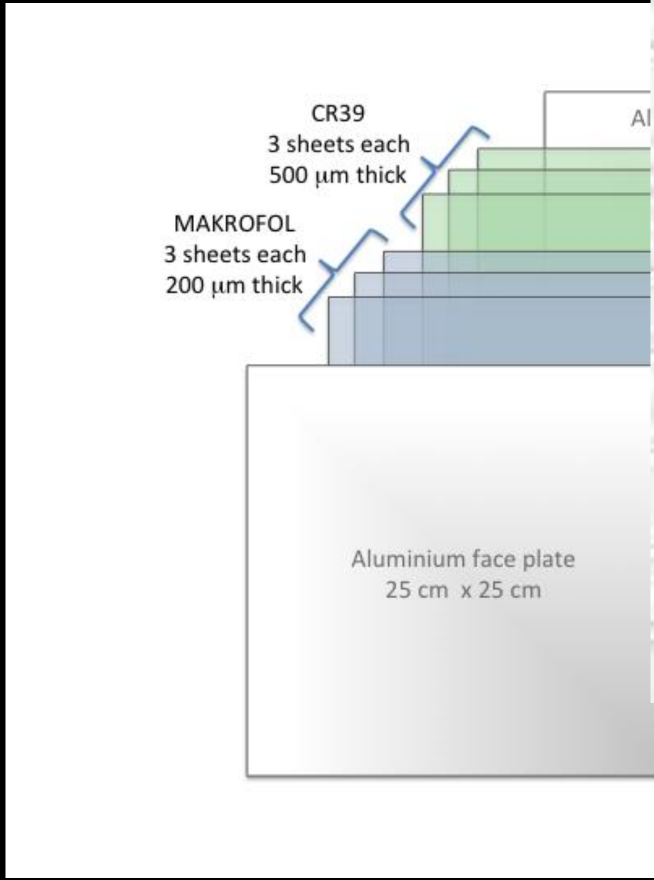
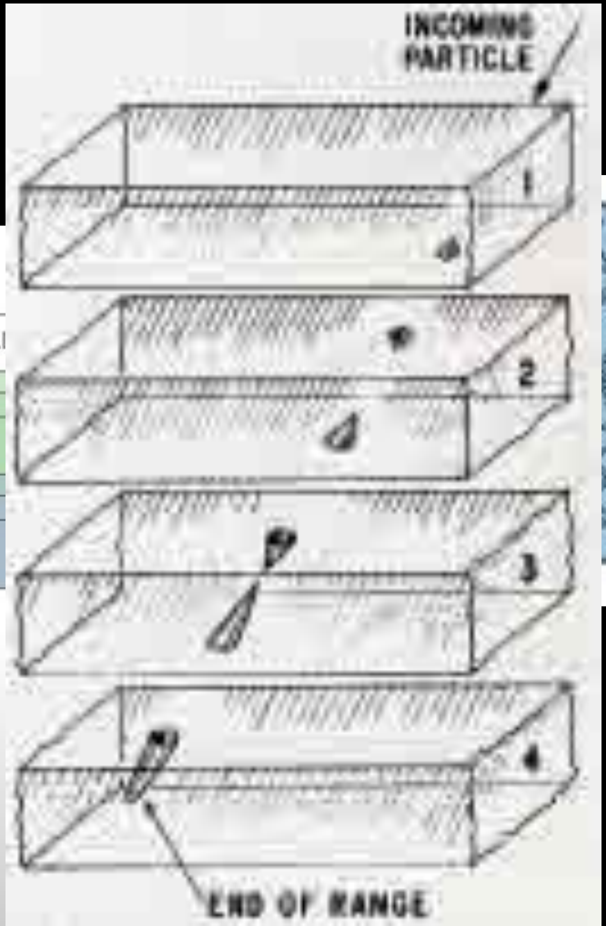
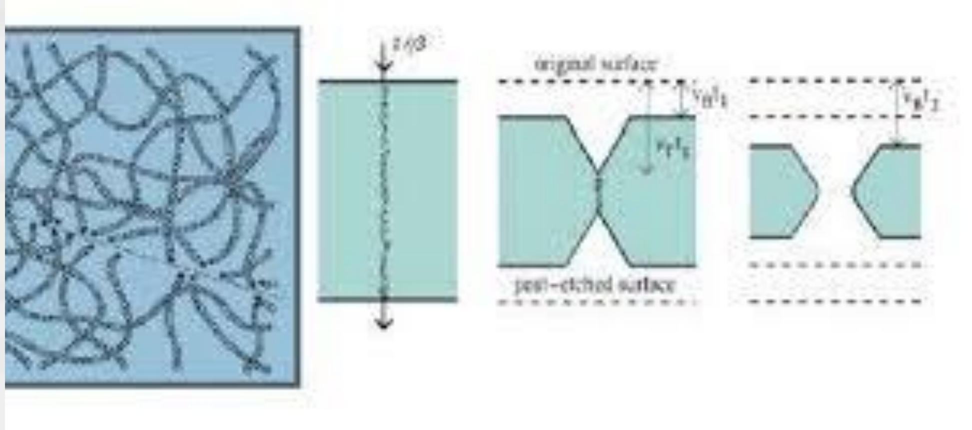
Nuclear Track Detectors



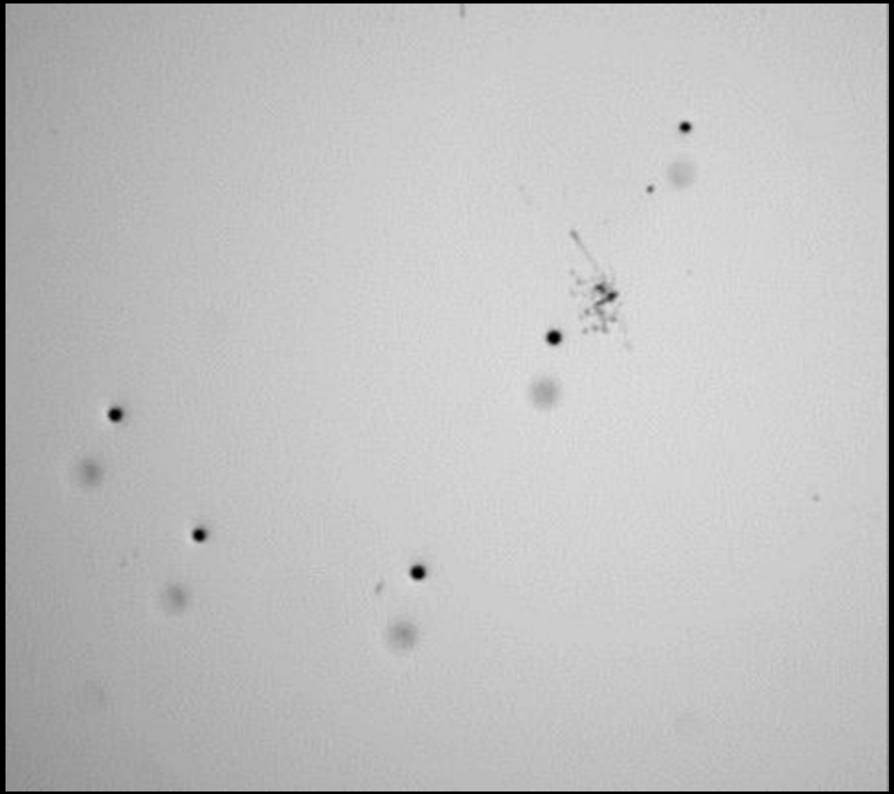




Expected SM particles will typically range-in / range-out in one or two sheets

Heavily ionising particles such as monopoles will cause damage all the way through

Nuclear Track Detectors



~1 mm^2 image of an NTD exposed to heavy ion beam to simulate exotic particle signature

Backlit illumination

Etch-pits reflect light away from the camera and appear as black circles

Blurred blobs are etch-pits on the reverse side of the clear plastic NTD – distance between them comes from the angle of incidence of the beam

Nuclear Track Detectors

~1 mm^2 image of an NTD exposed to heavy ion beam to simulate exotic particle signature

Brightfield illumination

Etch-pits reflect light away from the camera and appear as black circles

Blurred blobs are etch-pits on the reverse side of the clear plastic NTD – distance between them comes from the angle of incidence of the beam

Similar image for NTD exposed to the radiation environment around the LHC interaction point at IP:8

The Challenge…

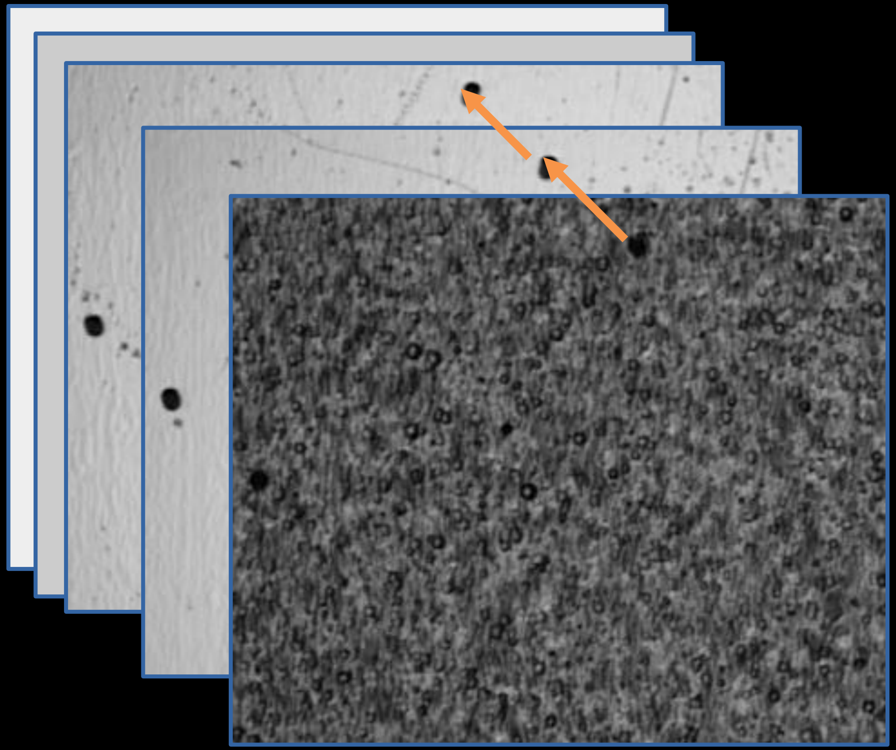
10s of m^2 of plastic to be scanned for etch pits

Humans are very good at spotting etch-pits but the process is labour intensive and time consuming

Can Machine Learning techniques be used to train a model that can predict etch-pit locations from scanned images?

This can be used to select interesting candidates for further inspection by a human

Data Sets

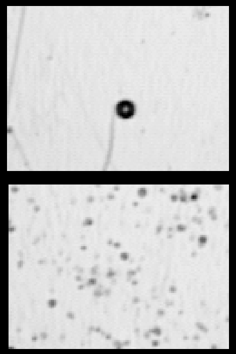


Five NTD foils exposed to Pb ion test beam

Front foil exposed at MoEDAL, + LHC bkg

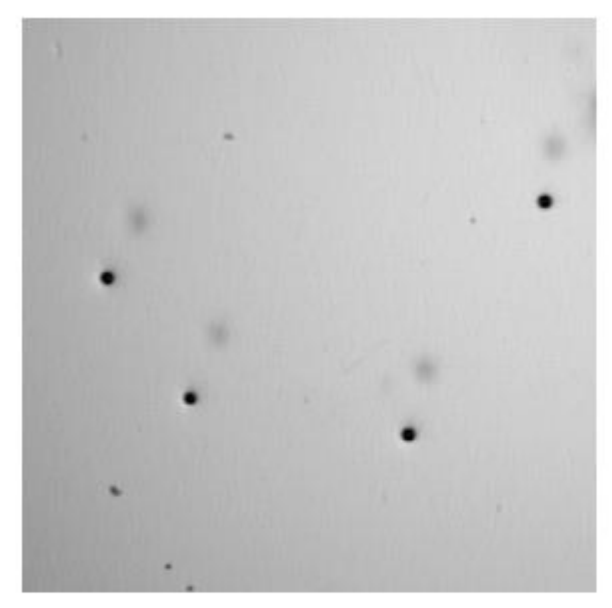
Can Identify etch-pits in unexposed foil trivially

Can map locations between exposed and unexposed foils providing a source of good labels

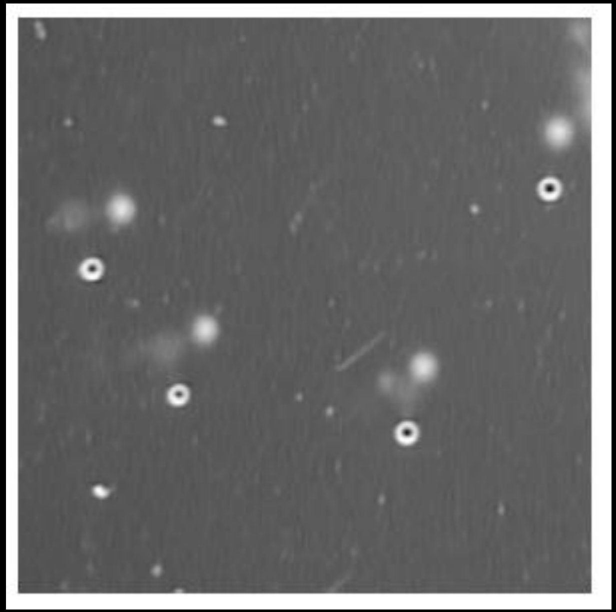


etch pits can be parametrised by quality eg, how many foils did the ion pass through: maintaining sensitivity to weaker ionisation /

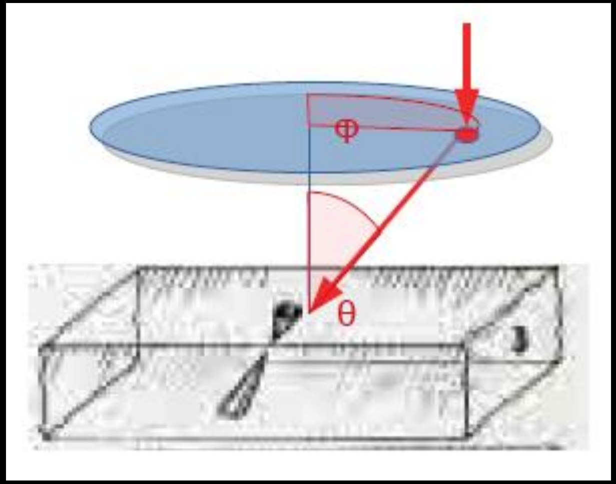
Data Sets - illumination



Backlit

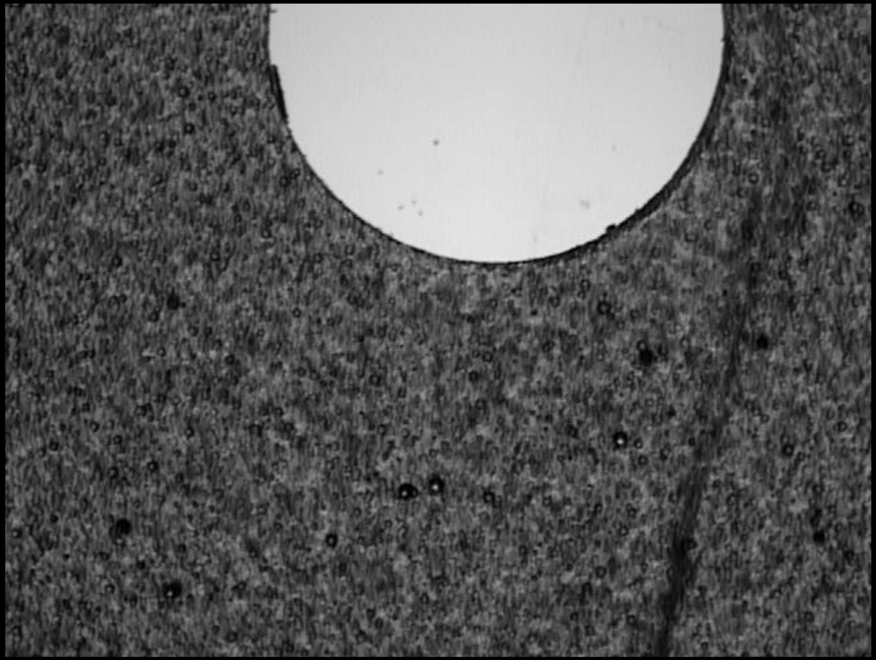


Dark field



Rotational

Alignment



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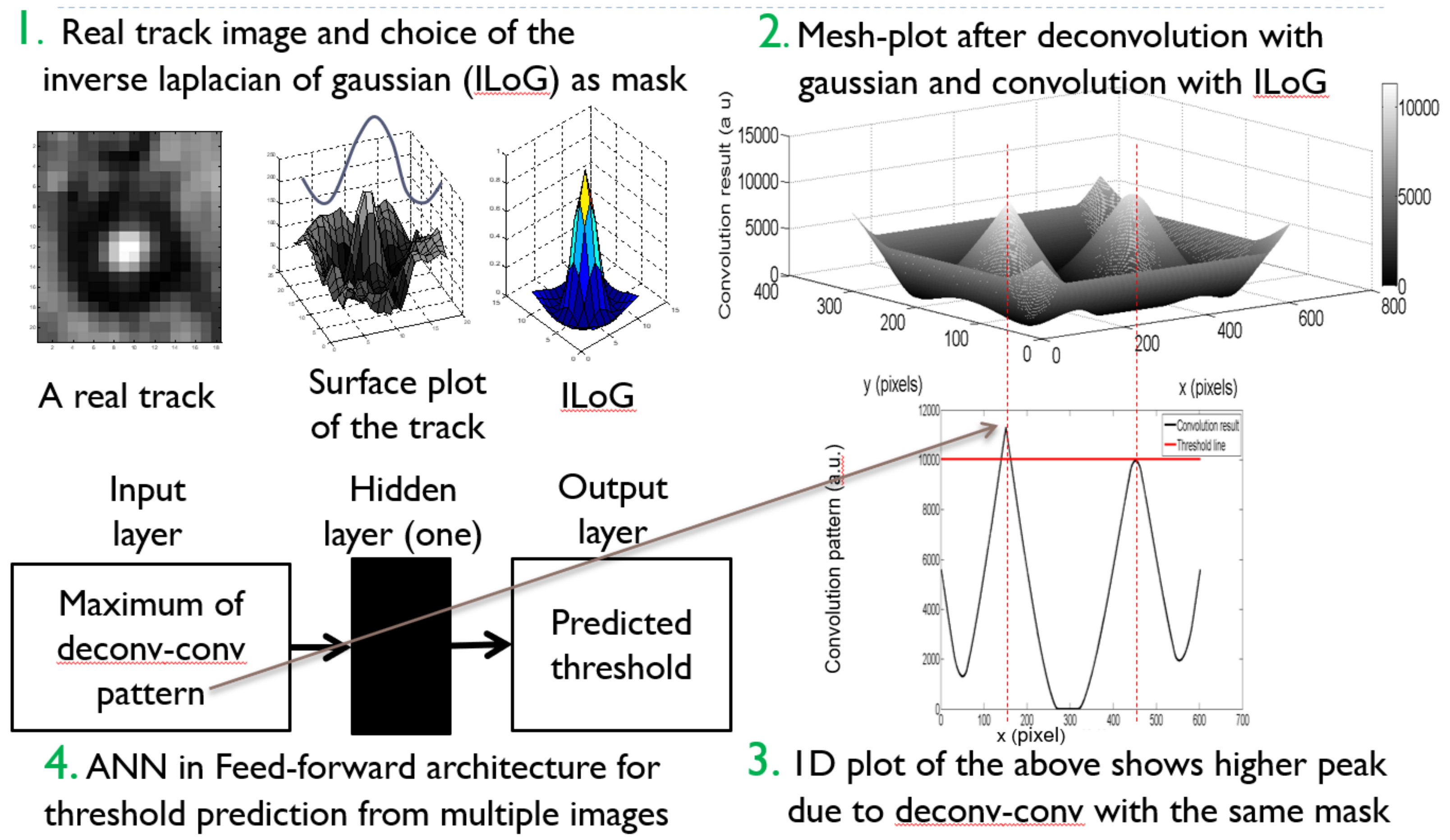
3 Alignment holes drilled through the stack to provide a way to realign them after etching

Aligning roughly by hand by overlaying the images gives sufficient resolution – 5 or 6 pixels

Method 1 : Sequential deconvolution and convolution followed by ANN

- Step 1
  - **Mask selection** using a suitable etch-pit (maximum area, nearly circular) from the image containing multiple etch-pits
  - **Deconvolution** of a new gaussian mask with the entire image
  - **Convolution** of the circular mask with the entire image which generates convolution peaks at the centre of each symmetric etch-pit (value of the peak depends on their common area)
  - **Manual threshold** for separation of etch-pits from noises
- Step 2
  - **Artificial neural network** used with two inputs – average of the image generated after deconv-conv and threshold values
  - **Predicted threshold as output** obtained after training which later applied to all other test images
  - **Marking** the actual etch-pits using morphological technique

Method 1 : Sequential deconvolution and convolution followed by ANN



2 - Joydeep Chatterjee *et al*, Application of Machine Learning on sequential deconvolution and convolution techniques for analysis of Nuclear Track Detector (NTD) images, arXiv:2005.07368, May 15, 2020

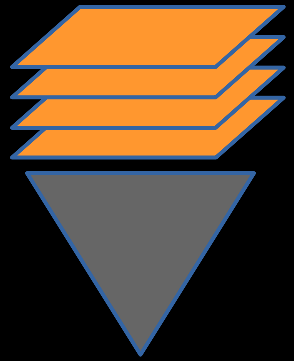
Works on whole single channel backlit images

ANN used to provide thresholding – can be done by hand but is labour intensive

Trained using hand labelled data

Method 2: Fully convolutional networks with transfer learning

Step 1: CNN Classifiers

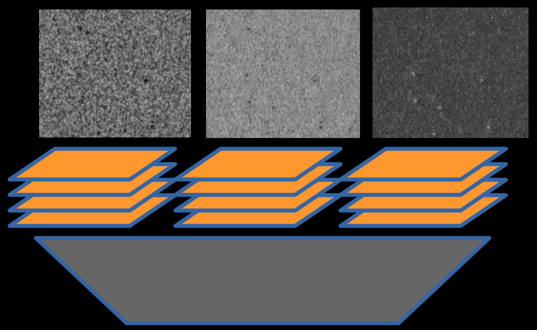


4 Convolution + pooling layers 4x4 kernel**

2 dense layers combine conv features into output score

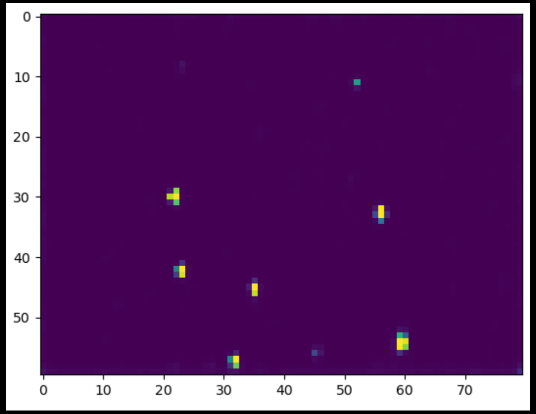
Train on 28x28 pixel images with and without etch pits with 5-folding

Combine CNNs from 5-fold + three lighting scenarios (backlit – 1 channel, darkfield – 1 channel, rotational 8-channels



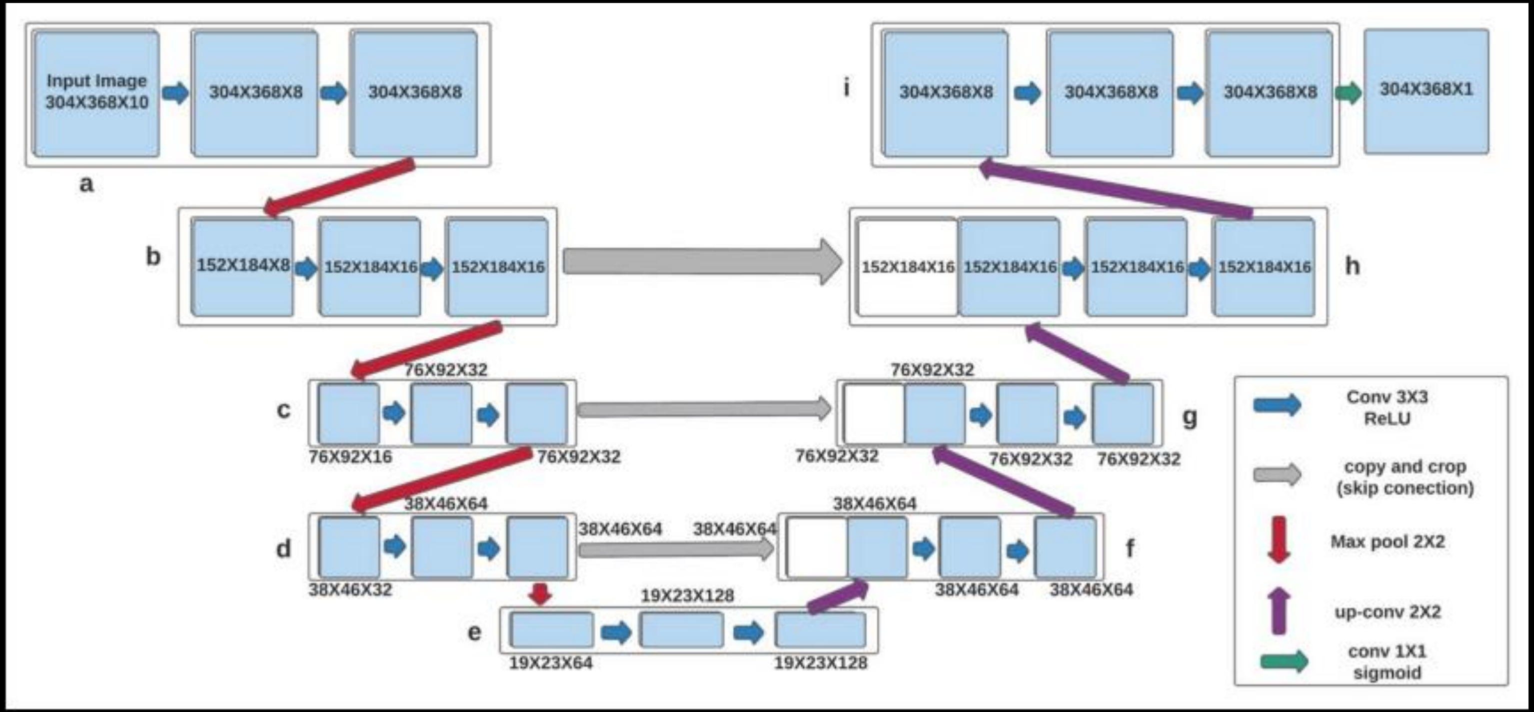
Use training from 28x28 pixel CNN classifiers but can be applied to any size image

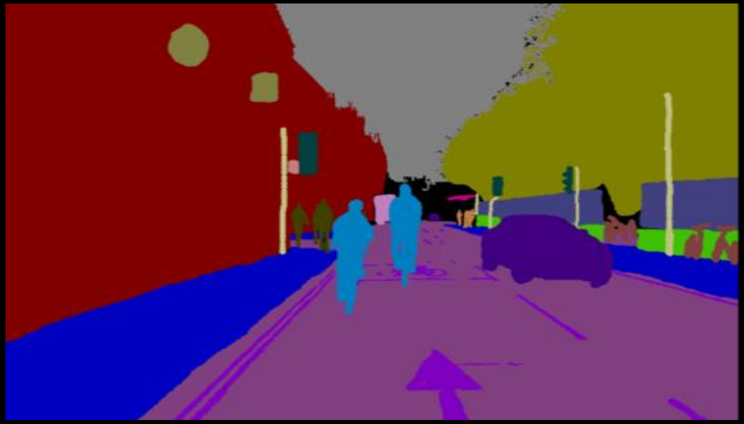
Step 2: ~Fully convolutional step



Step 3: Apply threshold and build segmentation map, etch-pit candidates are then in the middle of "hot-spots"

Method 3: Fully convolutional networks with U-Net architecture





Provides a method for image segmentation

See for example: **U-Net: Convolutional Networks for Biomedical Image Segmentation, Olaf Ronnerberger, Phillip Fischer, Thomas Brox,** Medical Image Computing and Computer-Assisted Intervention (MICCAI), Springer, LNCS, Vol.9351: 234--241, 2015

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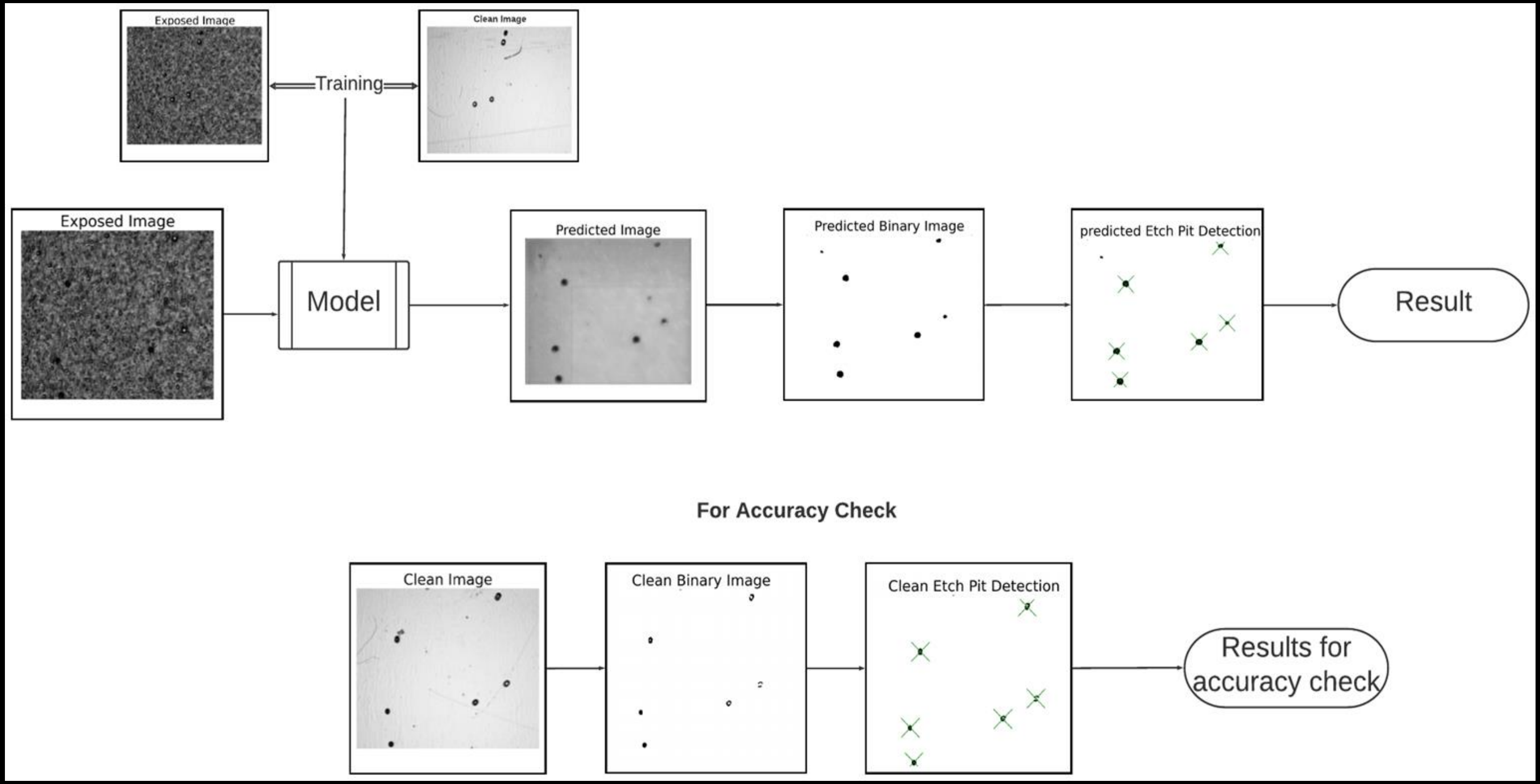

Train on a set of images with and without LHC background – full foil images with 9 channels

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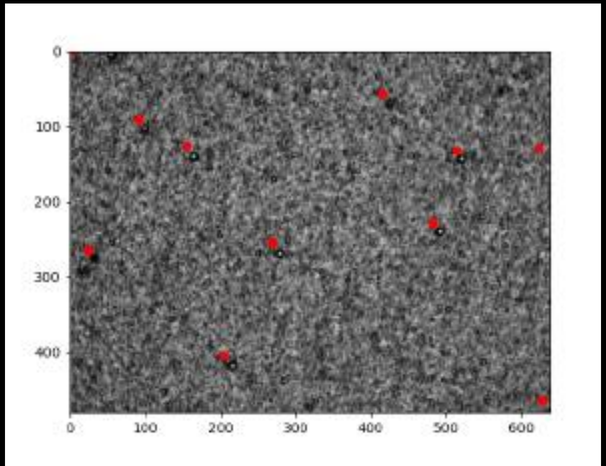
Preliminary Results
CNN Classifiers

Channel	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average	Std Dev
Backlit	97.29	96.45	97.08	97.50	97.29	97.12	0.36
Darkfield	99.79	99.79	99.16	99.38	99.58	99.54	0.24
Rotational	99.79	99.58	99.58	99.38	99.58	99.58	0.13

Table 7.6: Pb CNN validation accuracy % (fragments included in training data)



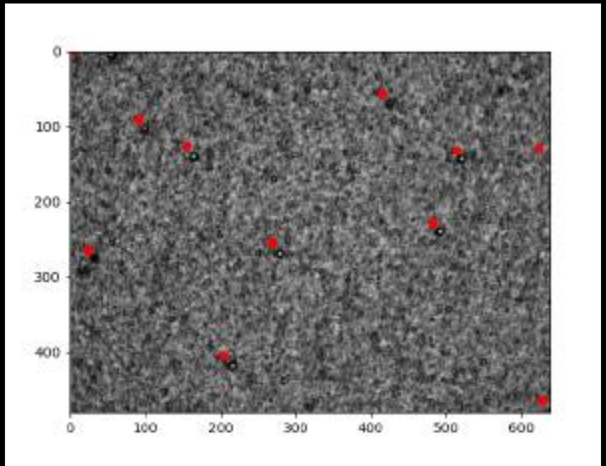
Channel	False positive rate	False negative rate
Backlit	2.41	3.33
Darkfield	0.50	0.42
Rotational	0.67	0.167

Table 7.9: False positive, False negative rates % (fragments included) 0.5 working point.

Performance evaluated on half of the data set kept aside for this purpose

Use spatial matching between “clean” and “exposed” sheets to measure FP and FN rates

Preliminary Results



	U Net	DCC	FCN (Simple)	FCN (Comb.)
True positives (correct detection)	1155	1046	980	1019
False positives (incorrect detection)	29	28	70	175
False negatives (Missed detections)	65	170	175	214
Total predicted	1184	1074	1050	972
Total true etch pits	1242	1242	1194	1194
Identification Eff	93%	84%	82%	85%

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Outlook

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Machine Learning techniques used to successfully identify etch pits

Work in progress:

Still working on harmonising the methods

Comparison of which candidates are misidentified by each algorithm

Evaluate the impact of the surface

Paper in preparation

Future Work

Run with automated scanning of images – could use candidate identification to do adaptive scanning – speed up the scanning process