Deep Convolutional Neural Networks applied to nuclear microprobe data

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Introduction

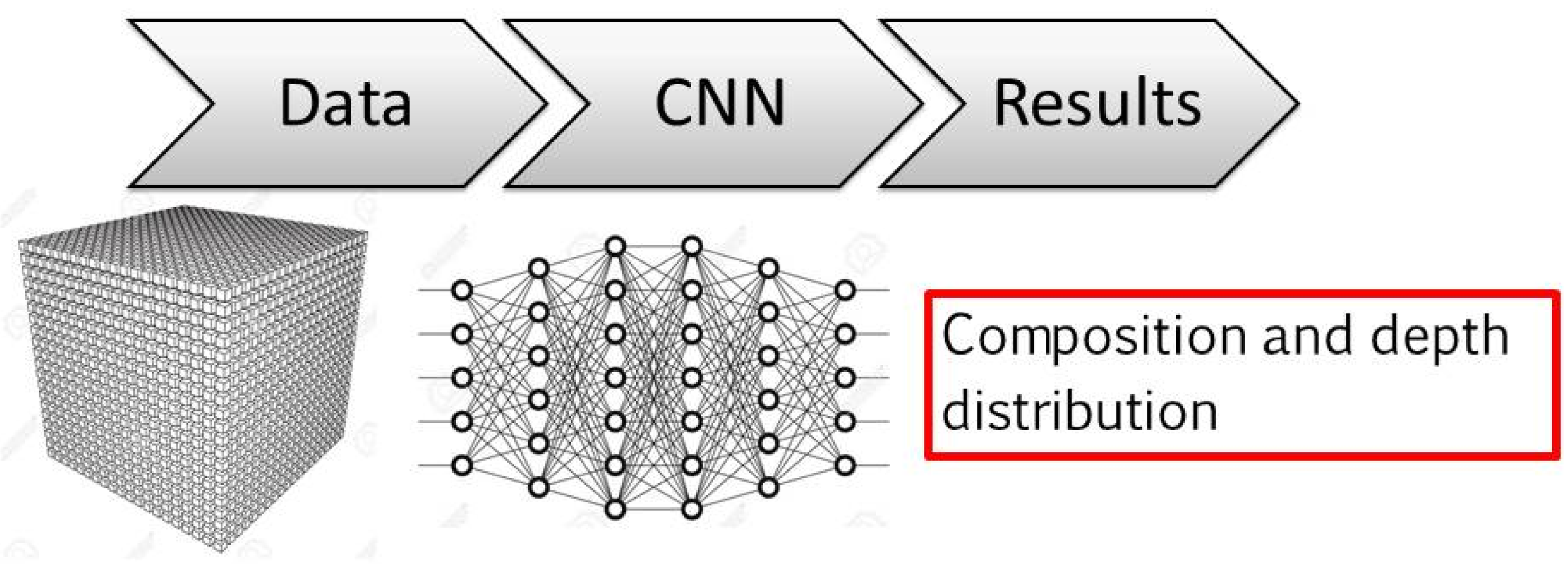
Typically, data from each area scanned by a nuclear microprobe is acquired as a 256 x 256 x *n* pixel matrix, each pixel containing *n* of the IBA spectra recorded during the experiment.

Although the average spectra of the map (the sum of all pixel spectra of each IBA technique) may show good counting statistics, when each pixel is considered individually, the corresponding single spectra usually have rather poor counting statistics.

Furthermore, try to individually fit all the 256x256 spectra recorded during a single run is an unacceptable time-consuming task.

Objective

Use deep Convolutional Neural Networks (CNN), which once trained, can handle the analysis of large data sets instantaneously.



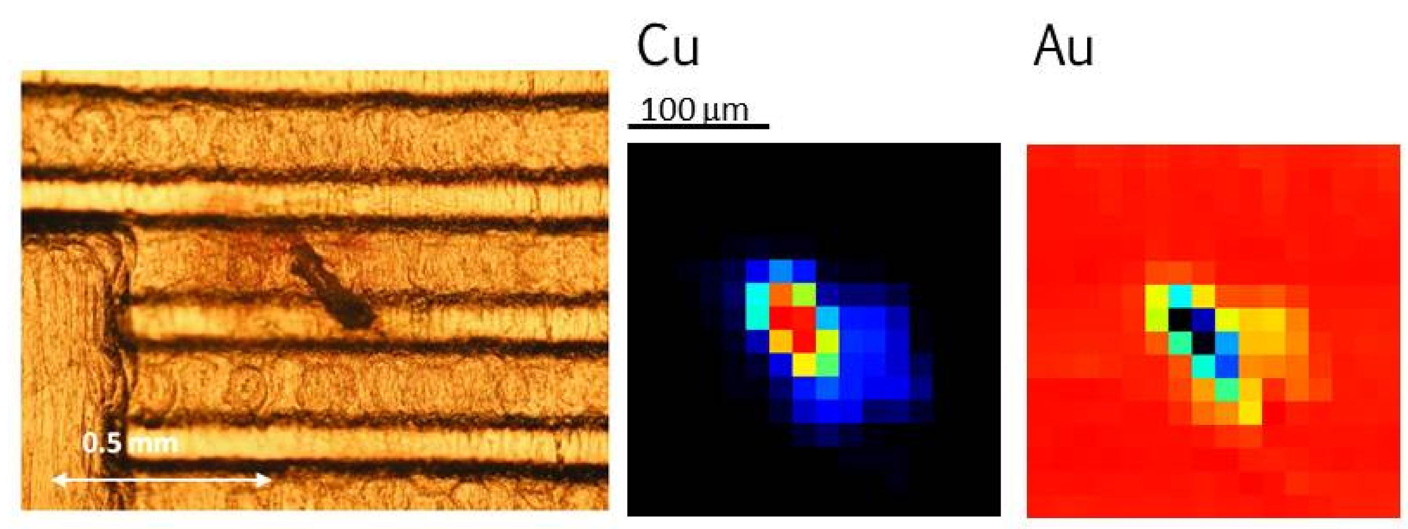
Data

Simulated RBS spectra with different concentration of copper and gold were obtained using the WiNDF code.

Poisson noise was added to these RBS spectra.

Real data were obtained using the Nuclear Microprobe at CTN-IST using a 2MeV proton beam. PIXE and RBS spectra were simultaneously recorded in *Listmode*.

Object: a pure gold coin with a copper rich agglomerate.



Acquisition time: 5 hours

The 256x256 RBS spectra were compressed (16x16) to increase the statistic. The number of RBS spectra to be analyzed would be 256 .

Convolutional Neural Networks (CNN) - Results

We have considered that the problem is a multi-Categorical classification problem in which each category (spectra) has distinct features that could be highlighted through the application of filters (starting point, peaks, and "shape" of the spectra).

Adding a convolutional layer increases the overall accuracy of the model. This layer creates a convolution kernel that is convolved with the input layer over a single spatial (or temporal) dimension to produce a tensor of outputs.

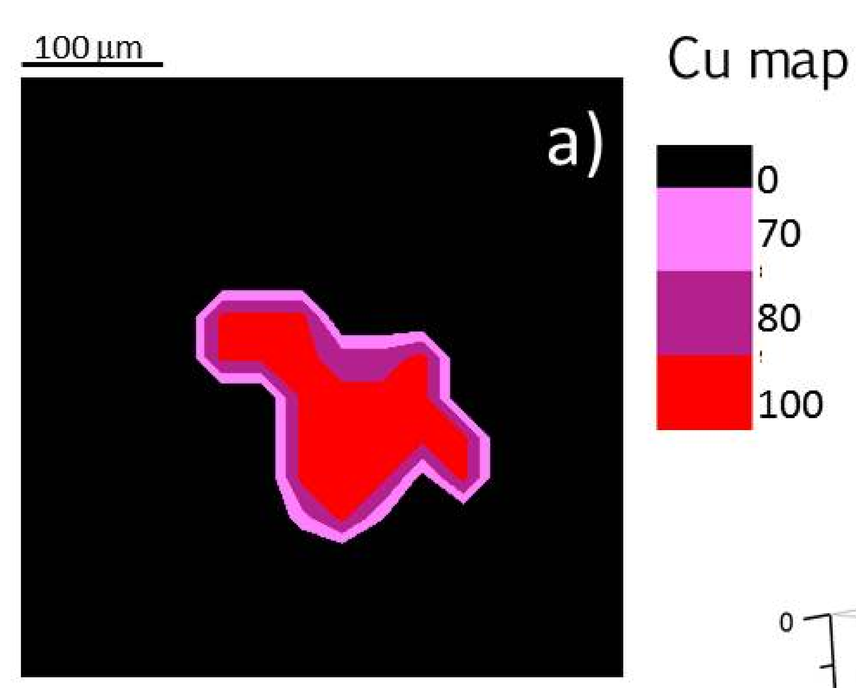
Multiple architectures were tested, obtaining different accuracy levels:

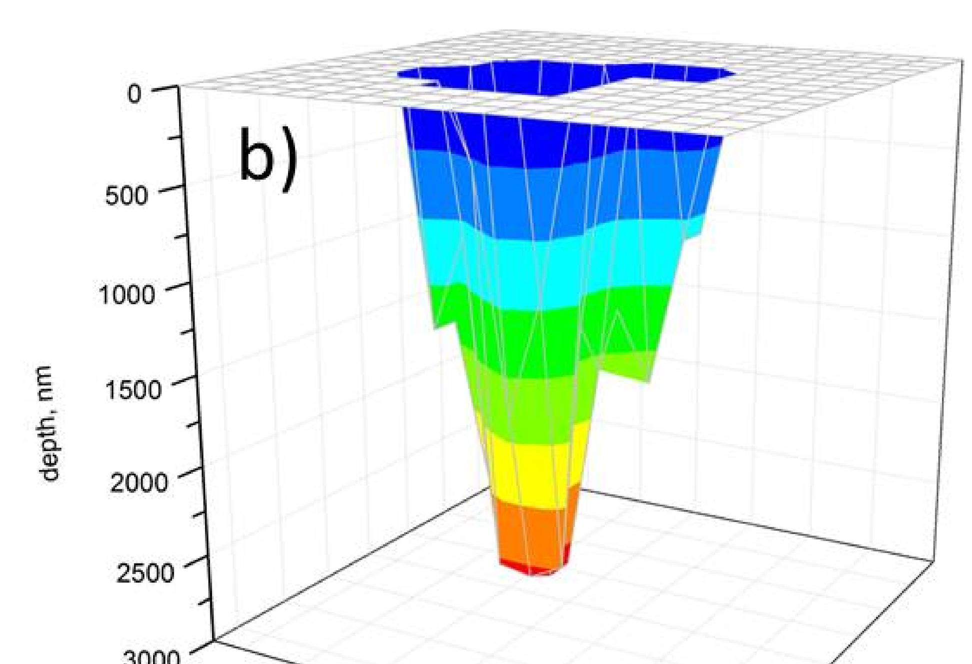
Architecture	Validation Split Accuracy
(I, C512, O)	83.66%
(I, C512, C256, O)	94.67%
(I, C512, C256, C128, O)	93.40%
(I, C512, C256, D64, O)	97.77%

I – Input
O – Output
D – Dense Layer
C – Conv layer

Representation of the outputs allows visualizing the concentration and compositional depth profile.

Cu map distribution: a) lateral; b) in-depth





Conclusions and Future work

Train the CNN is a time-consuming task, but after that, results are obtained almost instantaneously.

An improved model should increase the accuracy of the results. A proper interface to visualize results is under development.

This work will be useful for a future automated data analysis or automatic detection and characterization of non-homogeneous sample regions during the data acquisition, also providing accurate and on-line results.

References

[1] N.P. Barradas et al. Nucl. Instrum. Meth, B., 219-220 (2004) 105-109, https://doi.org/10.1016/j.nimb.2004.01.036.

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[3] N.P. Barradas et al. Physical Review E, 62 (2000) 5818-5829, https://doi.org/0.1103/PhysRevE.62.5818.