

Machine Learning-based Crystal Structure Prediction for X-Ray Microdiffraction

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Introduction:

X-ray diffraction (XRD) is an essential tool for phase identification and the characterization of crystal structure, impurity, strain, and texture. Conventional XRD yields only averaged results, and recent developments in micro- and nano-X-ray diffraction (μ XRD) with highly focused X-ray beams has enabled diffraction mapping characterization [1]. However, the bottleneck in the workflow of μ XRD experiments is the analysis of large XRD pattern dataset, most of the experiments using μ XRD are limited to point analyses, while the instruments are capable of diffraction mapping characterization that outputs tens of thousands of XRD patterns. A typical structural characterization using XRD needs to extract structural descriptors from the obtained patterns; the standard structural descriptors are crystal symmetry, space group, and lattice parameters. We attempted to predict the crystal structure from XRD patterns using machine learning (Fig. 1). This machine learning-based automated crystal structure prediction will contribute to the realization of on-the-fly data analysis in materials science.

Experimental:

A dataset with 188,607 XRD patterns was prepared by simulating the patterns of all materials in the Inorganic Crystal Structure Database (ICSD) [2] using Pymatgen middleware [3]. The XRD calculation was performed using Cu K α radiation (wavelength = 1.5418 Å) with the 2 θ range set to 0°–90°. We used the 2 θ positions of the ten peaks in ascending order of 2 θ , and the number of diffraction peaks as the descriptor for the patterns. We used random forests [4] to classify the XRD patterns into crystal systems and space groups. The prediction accuracy was estimated using 10-fold cross-validation.

Results and Discussion:

The prediction accuracy of the classification of the XRD patterns into space groups (230 classes) was 83.62%, which exceeded that achieved in a recent study using deep learning (81.14%) [5], although we used only ten 2 θ positions and the number of peaks as descriptors. The computational time for constructing the classification model using random forests was several minutes, and the classification of one XRD pattern took less than 1 ms. Further, we classified the XRD patterns based on crystal systems (seven classes) using random forests and achieved a prediction accuracy of 93.07% (Fig. 2).

In this study, we demonstrated that the crystal structures could be estimated from the peak positions of the XRD patterns using machine learning. It was shown that the performance of ensemble learning such as random forests was comparable to that of deep learning, with the former having a lower computational cost and higher speed. We also successfully predicted the lattice constants using random forest regression, which will be discussed in detail in the near future. Using the proposed method, a machine learning model could be constructed according to a specific experimental setup (i.e., depending on the 2 θ range or X-ray wavelength). Thus, we streamlined the materials discovery workflow, and the

accelerated characterization of materials will be realized by combining high-throughput experiments through optimal measurements [6] and on-the-fly data analysis (as shown in this research) and knowledge acquisition from the data [7].

References:

- [1] H B Qin *et al*, Environ. Sci. Technol. **51** (2017), p. 6027–6035.
- [2] <https://www.fiz-karlsruhe.de/en/leistungen/kristallographie/icsd.html>
- [3] S P Ong *et al*, Comput. Mater. Sci. **68** (2013), p. 314–319.
- [4] L Breiman, Mach. Learn. **45** (2001), p. 5–32.
- [5] W B Park *et al*, IUCrJ **4** (2017), p. 486–494.
- [6] T Ueno *et al*, npj Comput. Mater. **4** (2018), p. 4.
- [7] This work was partly supported by JST CREST JPMJCR1761.

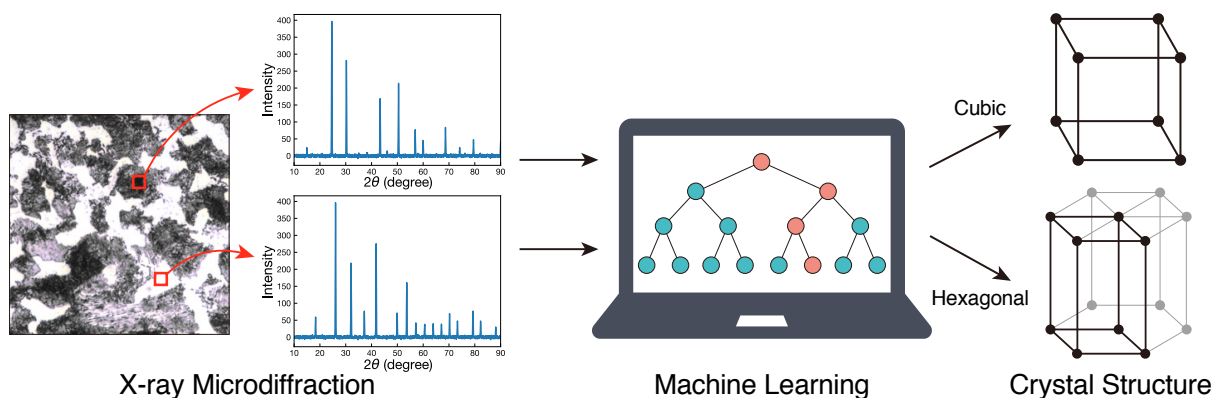


Figure 1. Schematic figure of machine learning methodology for crystal structure prediction of X-ray diffraction patterns. This methodology enables us the on-the-fly analysis of the obtained data, and spatially map a distribution of crystal structure combined with μ XRD.

								Accuracy	Number of data
Triclinic	4631	2416	166	49	31	20	48	62.9 %	7361
Monoclinic	752	27010	2270	129	58	30	1	89.3 %	30250
Orthorombic	88	2444	35825	494	136	111	57	91.5 %	39155
Tetragonal	7	83	813	28155	203	145	123	95.3 %	29529
Trigonal	3	76	393	235	17528	536	53	93.1 %	18824
Hexagonal	3	28	157	160	548	20783	36	95.7 %	21715
Cubic	17	2	24	60	32	29	41609	99.6 %	41773
	Triclinic	Monoclinic	Orthorombic	Tetragonal	Trigonal	Hexagonal	Cubic		

Figure 2. The accuracy of predicting crystal systems. The accuracy was evaluated with 10-fold cross-validation of the whole data. This performance is sufficient for the on-the-fly data analysis in high-throughput measurement such as μ XRD. It should be noted that 99.6 % classification accuracy in a cubic system was achieved.