23 February 2026

Battery Imaging Library: Multi-length scale and multi-modal synchrotron and laboratory battery imaging data for all

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Abstract

Battery research increasingly relies on advanced imaging, yet open access to such data remains rare, scattered across various sources, and difficult to find. The Battery Imaging Library (BIL) is the first open, curated collection of multi-modal and multi-length scale battery imaging datasets, accompanied by a searchable, FAIR-compliant website. Distinctive features include the release of raw experimental data (radiographs, sinograms, X-ray and electron diffraction patterns) together with rare operando and multi-resolution datasets. Each dataset is linked to Zenodo DOIs with metadata, ensuring persistence and citability; open-source Python scripts for preprocessing and reconstruction are also provided for various CT modalities. BIL enables algorithm benchmarking, machine learning, and teaching using experimental and industrially relevant data. By combining coverage across modalities, length scales, and chemistries with raw data accessibility and a FAIR-aligned web platform, the Battery Imaging Library provides a foundation for openness and reproducibility in battery imaging. The library is available here: https://www.batteryimaginglibrary.com

Keywords

tomography, imaging, batteries, x-rays, neutron, diffraction, microscopy, microct, nanoct, xrdct

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Abstract

Battery research increasingly relies on advanced imaging, yet open access to such data remains rare, scattered across various sources, and difficult to find. The Battery Imaging Library (BIL) is the first open, curated collection of multi-modal and multi-length scale battery imaging datasets, accompanied by a searchable, FAIR-compliant website. Distinctive features include the release of raw experimental data (radiographs, sinograms, X-ray and electron diffraction patterns) together with rare operando and multi-resolution datasets. Each dataset is linked to Zenodo DOIs with metadata, ensuring persistence and citability; open-source Python scripts for preprocessing and reconstruction are also provided for various CT modalities. BIL enables algorithm benchmarking, machine learning, and teaching using experimental and industrially relevant data. By combining coverage across modalities, length scales, and chemistries with raw data accessibility and a FAIR-aligned web platform, the Battery Imaging Library provides a foundation for openness and reproducibility in battery imaging. The library is available here: `https://www.batteryimaginglibrary.com`

1 Introduction

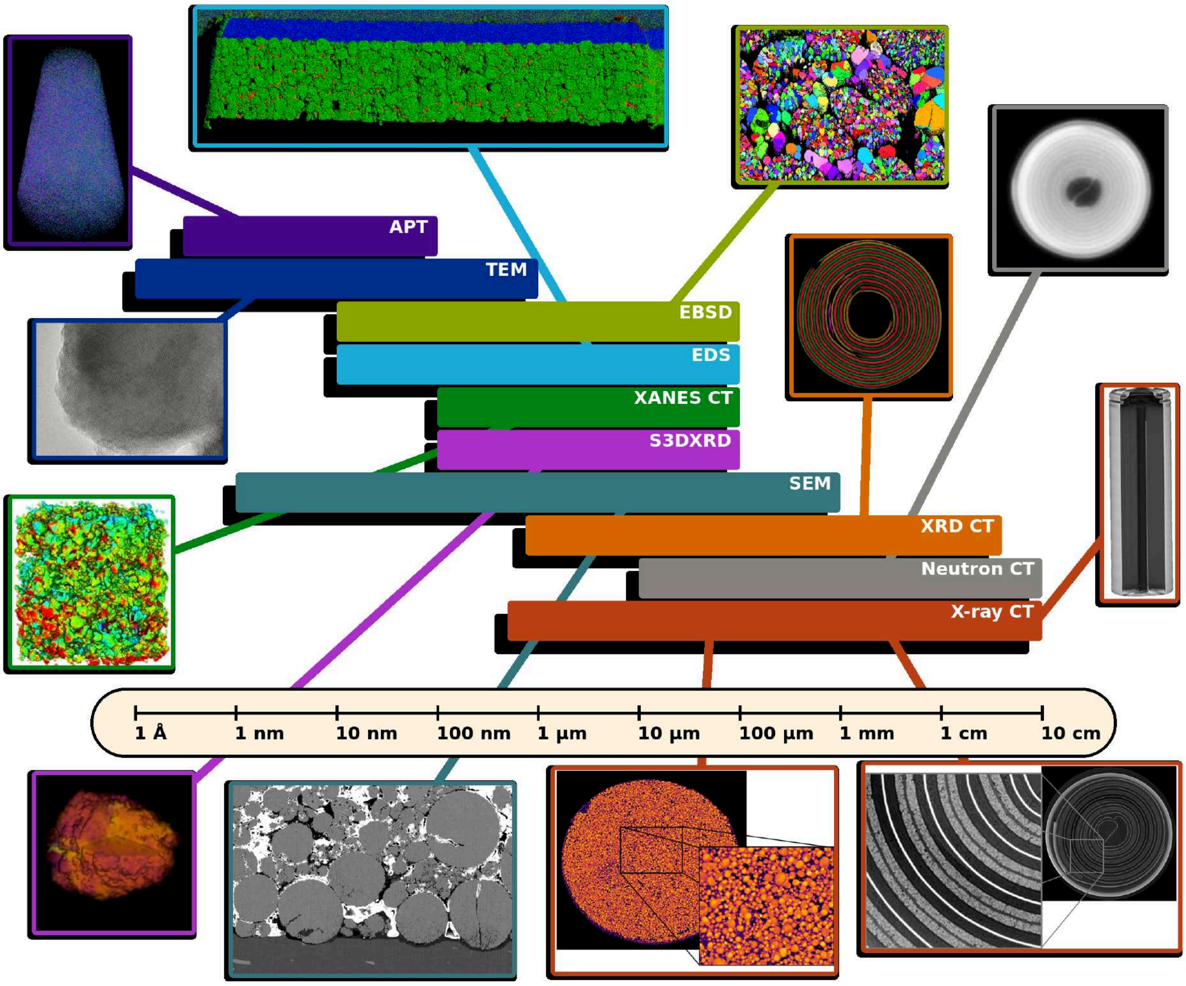

Figure 1: Illustration of the Battery Imaging Library (BIL) showing the breadth of imaging techniques and length scales included. The schematic highlights how datasets span from whole-cell imaging down to particle-level and crystallographic characterisation, reflecting the multi-modal nature of the library. Size ranges are reported from typical pixel/voxel size to largest practical scan size.

Imaging has become a cornerstone of modern battery research, enabling non-destructive, three-dimensional investigation of morphology, chemistry, and crystallography across multiple length scales [1, 2, 3]. From the level of individual active material particles to full commercial devices, imaging provides insights into processes such as particle cracking [4], porosity evolution [5], phase transitions, electrode delamination [6] and heterogeneous reaction dynamics [7]. These processes underpin the performance, safety, and lifetime of primary and rechargeable batteries, making imaging indispensable for both fundamental understanding and industrial optimisation.

Over the past two decades, the field has developed an extraordinary toolbox of imaging techniques. Laboratory micro-computed tomography (micro-CT) is now widely used to probe electrode structures and full-cell designs. Synchrotron-based X-ray methods, including high-resolution micro-CT, nano-CT, and diffraction-based imaging, enable insights into morphology, chemistry, and crystallography with temporal resolutions sufficient for operando studies. Complementary modalities such as neutron CT provide sensitivity to low-Z components (e.g. Li-based electrolytes) that are invisible to X-rays [8], while electron microscopy combined with chemical mapping, like scanning electron microscopy (SEM) with energy dispersive X-ray spectroscopy (EDS) and electron backscatter diffraction (EBSD), can resolve nanoscale morphology, elemental distributions, and crystallography. Collectively, these methods constitute the state-of-the-art in characterising electrochemical energy storage systems.

Despite the ubiquity of these approaches in academic and industrial research, access to imaging data remains highly restricted. Most published studies do not release their underlying datasets, or only provide reconstructed volumes stripped of radiographs, sinograms, or spectral information (e.g. EDS). These omissions preclude reproducibility and prevent realistic benchmarking of reconstruction, denoising, segmentation, or machine learning methods. Informal access via direct correspondence with authors is inequitable, often unsuccessful, and unsustainable as a mechanism for community sharing.

Existing repositories are limited in certain aspects. Large datasets tend to be instrument specific: TomoBank [9], CCPi [10] and FIPS [11] datasets for X-ray tomography or the EMBD [12], Warwick EM [13] and Aversa et. al [14] datasets for electron microscopy. These often do not include raw data (sinograms, spectra, diffraction patterns etc.), and datasets which do - often for algorithmic benchmarking - tend to be of specific materials (walnuts, lungs, etc.) [15, 16, 17]. Battery imaging data tends to be fragmented single-sample records, and although others works like the National Laboratory of the Rockies' battery microstructure library [18], or the Glimpse platform [19] are more general and offer more accessible entry-points, they are still instrument-specific. As a result, whilst valuable within their domains, these resources do not capture the full multimodal and multi-length scale landscape of modern battery imaging, nor do they enable reproducible analysis pipelines from raw detector data.

To address this unmet need, we introduce the *Battery Imaging Library* (BIL): the first open, curated repository that combines multi-modal and multi-length scale coverage with raw data and industrially relevant samples. BIL spans multiple complementary imaging modalities, specifically laboratory and synchrotron X-ray micro-CT, laboratory and synchrotron X-ray nano-CT, neutron-CT, synchrotron X-ray powder diffraction CT (XRD-CT), synchrotron multigrain 3D scanning three-dimensional X-ray diffraction (3D-S3DXRD), synchrotron 3D X-ray absorption near edge structure CT (3D XANES-CT), laboratory atom probe tomography (ATP) and 2D/3D FIB-SEM/EDS/EBSD, covering full commercial cells, electrodes, and individual particles. Critically, the library consistently includes raw data (radiographs, sinograms, X-ray diffraction patterns, EBSD Kikuchi patterns), enabling complete analysis pipelines and supporting algorithmic innovation.

BIL includes a dedicated website (`https://www.batteryimaginglibrary.com`), which provides a searchable interface for exploring datasets by size, modality or chemistry. Each dataset is linked to a Zenodo DOI and enriched with metadata, ensuring persistence, citability, and compliance with FAIR (Findable, Accessible, Interoperable, and Reusable) principles [20]. This web-based platform directly addresses a key barrier in the field: the absence of any reliable way to search for or retrieve battery imaging datasets. By lowering the barrier to entry, the website makes BIL accessible not only to specialists, but also to educators, students, and developers from adjacent fields such as computer vision and AI.

BIL has three primary goals:

- **Democratising data**: making state-of-the-art imaging data available without restriction, lowering barriers for both early-career researchers and established groups.
- **Enabling method development**: providing complete, realistic datasets for algorithmic benchmarking in reconstruction, denoising, segmentation, super-resolution, spectral unmixing, and multimodal data fusion.
- **Supporting education and training**: equipping educators and students with open datasets and reproducible workflows that allow hands-on exploration of imaging methods in undergraduate, postgraduate, and professional training contexts.

We present a summary of the initially data available in BIL in Table 1, reporting the number of scans, dataset size and range of voxel sizes for each modality.

2 Scope and Coverage of the Library

The Battery Imaging Library covers imaging across different modalities, length scales, and chemistries, with emphasis on commercially relevant devices and realistic experimental conditions. Its datasets are grouped into three broad scales of observation: whole-cell imaging, electrode-level imaging, and microstructural/crystallographic imaging (see Figure 1).

Whole-cell imaging

BIL includes datasets for commercial cylindrical cells spanning the most widely used battery chemistries: lithium-ion (Li-ion), sodium-ion (Na-ion), nickel–metal hydride (NiMH), lithium iron disulfide (Li/FeS_2) and alkaline zinc–manganese oxide (Zn–Mn) (see Figure 2). These cells are imaged using laboratory and synchrotron X-ray micro-CT, synchrotron XRD-CT, and, in one case, neutron CT (Li-ion NMC532) [21, 22]. The inclusion of neutron-CT data is particularly

Table 1: Summary of the current data in BIL, broken down by modality.

	Number of experiments	Dataset size (GB)	Pixel/Voxel size range (μm)
Neutron-CT	7	29.8	29.0 - 55.0
Synchrotron X-ray micro-CT	22	1990	3.24 - 18.53
Synchrotron X-ray nano-CT	9	1010	0.55 - 1.10
Synchrotron XRD-CT	23	255	10.0 - 40.0
Synchrotron S3DXRD	1	16.2	0.125
Synchrotron 3D XANES-CT	1	126	0.046
Laboratory X-ray micro-CT	20	358	9.00 - 40.0
Laboratory X-ray nano-CT	16	11	0.064 - 0.128
SEM	11	24.5	0.00480 - 0.0843
EDS	8	3.88	0.0405 - 0.225
EBSD	6	303	0.100-0.150
TEM	3	1.7	0.0079
APT	1	0.85	N/A
Total	**128**	**4127**	**0.00480 - 55.0**

valuable, as it is rarely available to the battery community and provides complementary contrast to X-rays for light components in Li-ion batteries (e.g. Li-based electrolytes and the location of the Li species in general within the cell). By including neutron CT alongside X-ray modalities, BIL enables multimodal comparisons and supports the development of cross-domain data fusion strategies. Furthermore, BIL includes XRD-CT scans of a battery of each chemistry in at least two different states of charge.

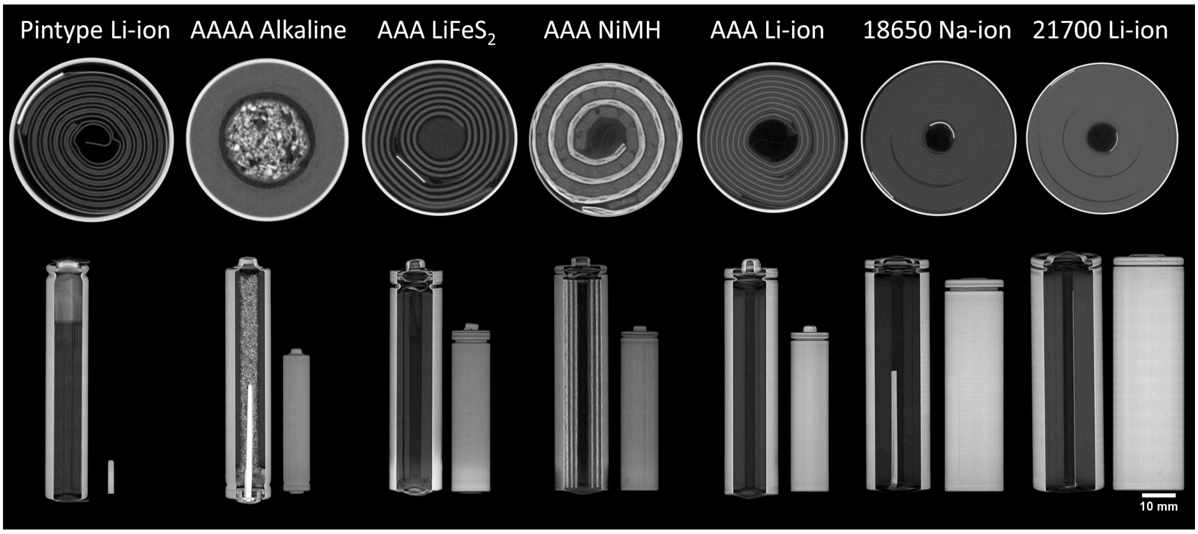

Figure 2: Example laboratory cone-beam X-ray micro-CT reconstructions of commercial cylindrical cells covering a range of form factors and chemistries (Li-ion, Na-ion, NiMH, Li/FeS_2, Zn–Mn). These datasets allow comparison of structural design choices between chemistries and are representative of the realistic, industrially relevant samples included in BIL.

Electrode and particle imaging

At the electrode and particle level, BIL focuses on the widely deployed $LiNi_{0.8}Mn_{0.1}Co_{0.1}O_2$ (NMC811) cathode material. This system is imaged using synchrotron and laboratory X-ray nano-CT, synchrotron S3DXRD, as well as 2D and 3D FIB-SEM/EDS/EBSD data. Nano-CT captures nanoscale porosity and particle morphology, whilst S3DXRD resolves crystallographic heterogeneity in primary particles (grains) within a secondary particle. The FIB-SEM/EDS data offer morphological and chemical information at sub-micron resolution in three dimensions. These correlated scans enable method development, for example new segmentation approaches using multi-modal imaging data as input. BIL contains several datasets of SEM and X-ray nano-CT of pristine and cycled NMC111 and NMC811 electrodes under different conditions [23, 24]. It should be noted that BIL also contains imaging datasets from other electrode materials, such as high resolution 2D FIB-SEM/EDS data of Si-graphite negative electrodes and a challenging to acquire synchrotron 3D XANES-CT of a $LiCoO_2$ electrode.

Microstructural and crystallographic imaging

At the microstructural and crystallographic scale, BIL contains 2D and 3D EBSD datasets of NMC811, with both indexed orientation maps and raw Kikuchi diffraction patterns. To our knowledge, this represents the first openly available EBSD dataset for a battery material, and uniquely, the first to include raw Kikuchi patterns. This enables the development and benchmarking of orientation indexing algorithms and the training of deep learning models directly on diffraction patterns rather than pre-processed maps. Together with corresponding 2D SEM/EDS, these datasets enable multimodal correlation between structure, chemistry, and crystallography. Furthermore, BIL includes a synchrotron S3DXRD dataset of a single NMC811 particle which, to the best of our knowledge, is also the first application of S3DXRD on a battery electrode material. Last but not least, BIL includes TEM images [25, 26], in one case coupled with EDS data for a $LiFePO_4$ electrode as well as APT data from an NMC811 material.

Raw experimental data

A defining feature of BIL is the consistent inclusion of raw data (see Figure 3). For the neutron-CT and synchrotron X-ray micro and nano-CT datasets, this includes radiographs / sinograms alongside reconstructed volumes. For EBSD, it includes raw Kikuchi patterns, not only indexed orientation data. BIL also includes the raw and processed data from a 3D-S3DXRD dataset of a single particle, as well as raw XRD-CT data from one cylindrical battery (i.e. the full set of raw 2D diffraction patterns). Furthermore, BIL includes the raw data from a 3D XANES-CT of a $LiCoO_2$ cycled electrode as well as the raw radiograph data from two laboratory X-ray nano CT datasets (i.e. pristine uncalendered and end-of-life after ca. 1000 cycles NMC811 electrodes). This level of completeness is rare in battery imaging and enables fully reproducible pipelines, realistic benchmarking of reconstruction and denoising algorithms, and the application of self-supervised learning approaches that exploit raw, unlabelled data.

Datasets from 4D and 5D experiments

BIL also includes rare *operando* datasets, such as synchrotron X-ray micro-CT and XRD-CT acquired during galvanostatic discharge of commercial $LiFeS_2$ and Zn–Mn cells (see Figure 4 and Figure 5). These datasets capture dynamic degradation processes in four dimensions (3D spatial + 1D time), providing opportunities for the development of time-resolved segmentation, tracking, and AI-based forecasting methods. Importantly, BIL includes the data from a 5D tomographic diffraction imaging experiment (3D spatial + 1D diffraction + 1D potential) using a Panasonic CG-320A pintype Li-ion battery (see Figure 6) [27, 28, 29]. In addition, BIL provides multi-resolution CT datasets acquired at varying exposure times and dose levels. These support research on dose optimisation, super-resolution, and domain adaptation, and to our knowledge represent the first openly available multi-resolution CT datasets for batteries.

Multi-modal complementary datasets

BIL offers complementary datasets, such as X-ray micro—CT with XRD-CT and / or neutron CT of the same cell, or SEM with EDS and EBSD of the same electrode. This allows holistic analysis of morphology, chemistry and crystallography, potentially across length-scales. These datasets also enable development and benchmarking of correlative algorithms like registration, data fusion [30] and guided upsampling.

3 Processing Pipelines, Website Design and Data Access

The BIL website (`https://www.batteryimaginglibrary.com`) provides a user-friendly interface for viewing, searching, and accessing the library's data. Each scan has a small tile with a representative preview image and key summary information. These tiles link to a page which includes information on scan parameters, citation details and links to Zenodo DOIs hosting the data (raw, reconstructed, processed *etc.*). The website's aim is to provide searchable, intuitive access for non-specialists. Figure 7 shows an example screenshot of the website's search page.

The library was designed to be easily extensible via community contributions: researchers can contribute datasets by depositing them on Zenodo and submitting the DOI (or the DOI of a relevant paper) alongside other associated data. Zenodo was chosen as the primary hosting for its generous upload limits and institutional backing, ensuring data will always be accessible and archived. Furthermore, there is a dedicated Zenodo community for all uploaded BIL Zenodo entries (`https://zenodo.org/communities/batteryimaginglibrary/`).

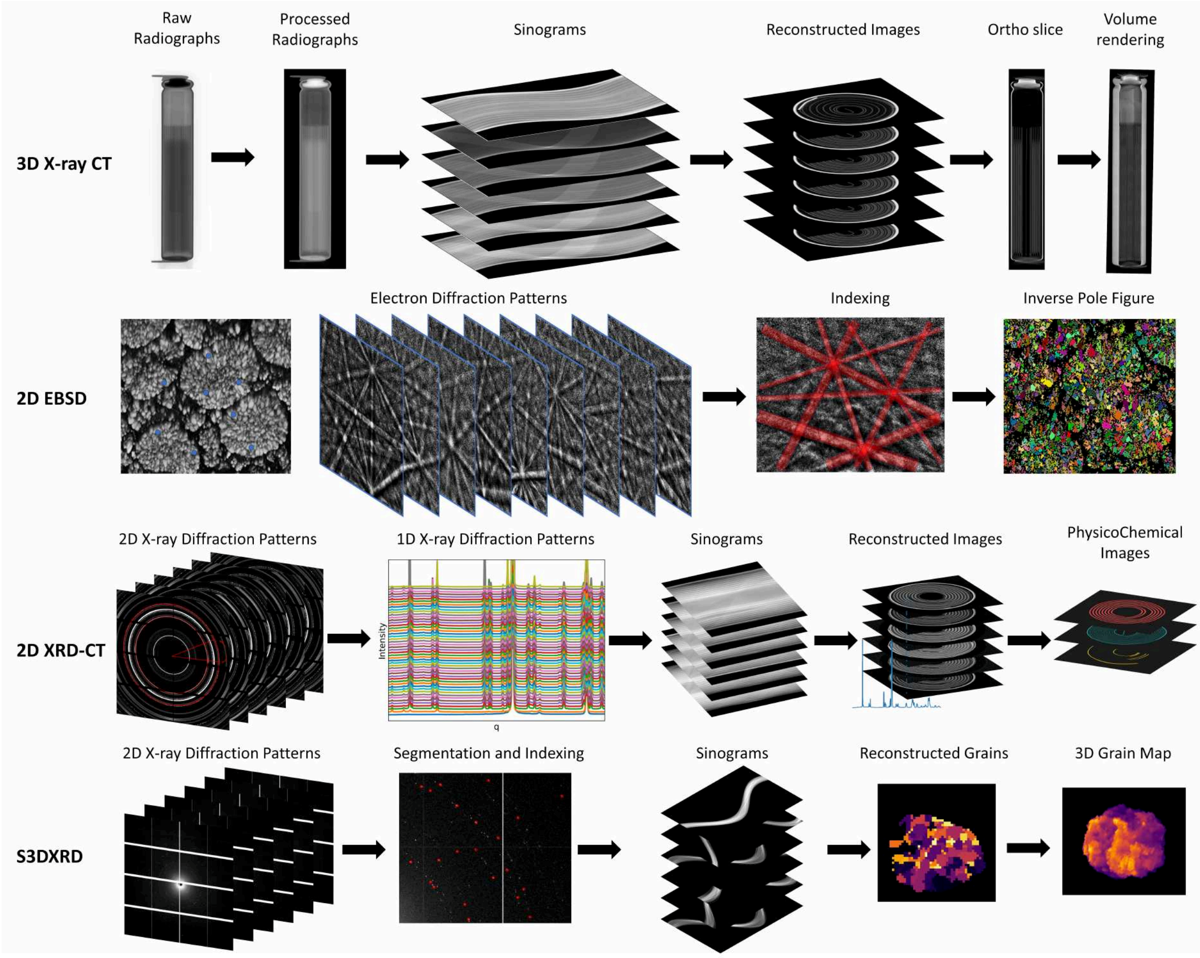

Figure 3: Examples of raw experimental data types made openly available through BIL. Shown are radiographs from X-ray micro-CT, Kikuchi diffraction patterns from EBSD, diffraction frames from S3DXRD, and 2D diffraction patterns from XRD-CT. Providing these raw data alongside reconstructions ensures reproducibility and supports algorithm development.

BIL includes open-source Python tools designed to make multimodal imaging data accessible and reproducible. These tools cover preprocessing, normalisation, sinogram data handling, and tomographic image reconstruction for synchrotron parallel beam X-ray CT and neutron-CT data, pencil beam XRD-CT, as well as laboratory cone-beam X-ray CT data. Jupyter notebooks demonstrate end-to-end workflows, allowing users to reproduce complete imaging pipelines from raw experimental data to reconstructed images. The laboratory cone beam X-ray CT data are reconstructed using the Core Imaging Library [31, 32] while the rest are handled using nDTomo [33] and ASTRA Toolbox [34]. All these notebooks, as well as the website source code, are available on the BIL github repository. The tools build on the *nDTomo* framework for diffraction tomography, extending its functionality to multimodal datasets. They are particularly suited for pedagogy, enabling students to engage with real imaging data and replicate complete processing workflows.

4 Use Cases and Applications

The Battery Imaging Library is intended to support a broad range of applications:

Algorithm benchmarking: the inclusion of raw data provides a rigorous testbed for algorithmic development. Researchers can benchmark new methods for CT reconstruction, noise suppression, and spectral analysis against realistic data that reflect the challenges of industrially relevant systems rather than idealised toy examples. Difficult-to-acquire datasets like experimental XRD-CT of cylindrical cells offer the unique opportunity to work on algorithms that solve data problems caused by self-absorption and parallax artefacts [35, 36, 37]. The availability of multi-resolution and multi-dose datasets allows systematic comparison of algorithms across data quality regimes, while overlapping modalities enable benchmarking of registration and fusion methods.

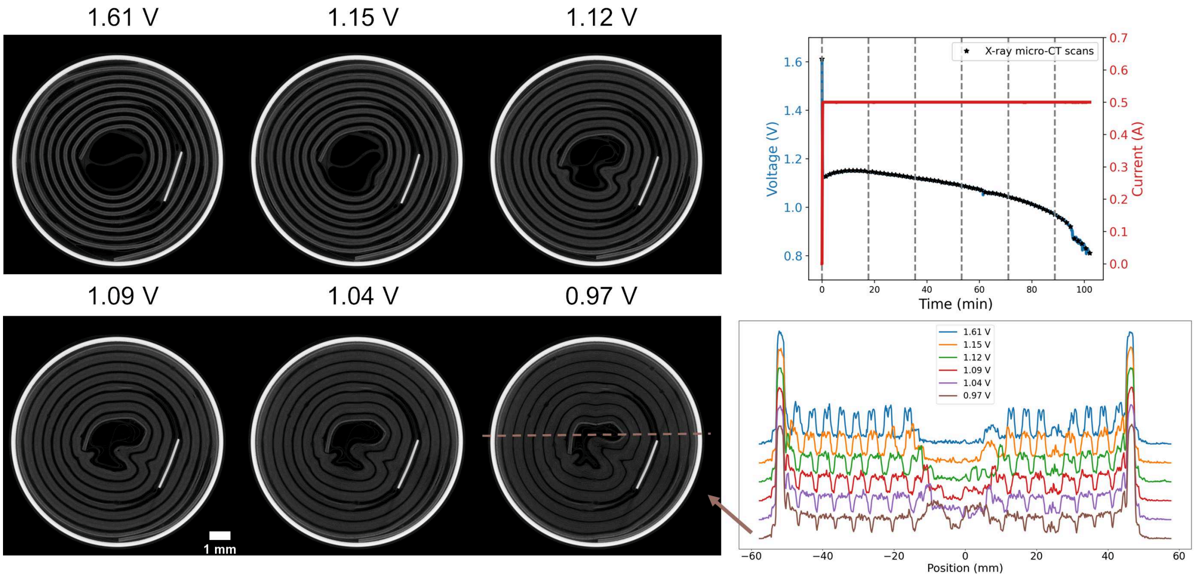

Figure 4: Time-resolved X-ray micro-CT dataset acquired operando during the galvanostatic discharge of a commercial $LiFeS_2$ primary cell. The experiment captures internal structural changes such as porosity formation and electrode degradation, providing a rare 4D dataset (3D + time) for dynamic battery processes.

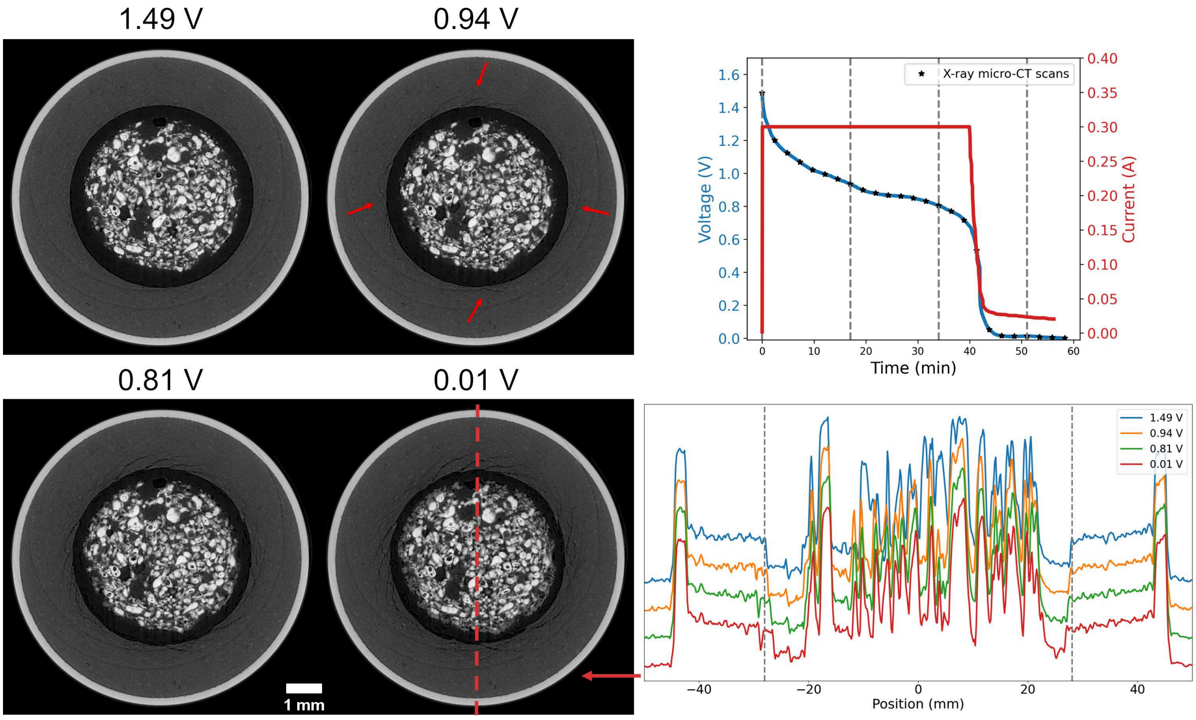

Figure 5: Operando X-ray micro-CT of a commercial alkaline Zn–Mn cylindrical cell under discharge conditions. The dataset reveals dynamic changes in electrode structure and morphology, serving as a benchmark for developing time-resolved segmentation and tracking methods.

Machine learning: BIL offers an unprecedented opportunity for the development of machine learning models in battery imaging. Multi-resolution data can be used to train and validate super-resolution networks, bridging low-dose and high-quality reconstructions. Multimodal datasets enable the exploration of domain adaptation strategies, for example transferring models trained on X-ray CT to neutron CT or SEM/EDS data, AI-driven data fusion, or the learning of structure–chemistry–property relationships across scales. Raw data are particularly suited to self-supervised learning, where large volumes of unlabelled data can be exploited to train models for segmentation, reconstruction, or hyperspectral image analysis. The inclusion of raw data from modalities such as EBSD Kikuchi patterns and 3D-S3DXRD also provides opportunities for applying deep learning to diffraction-based imaging techniques.

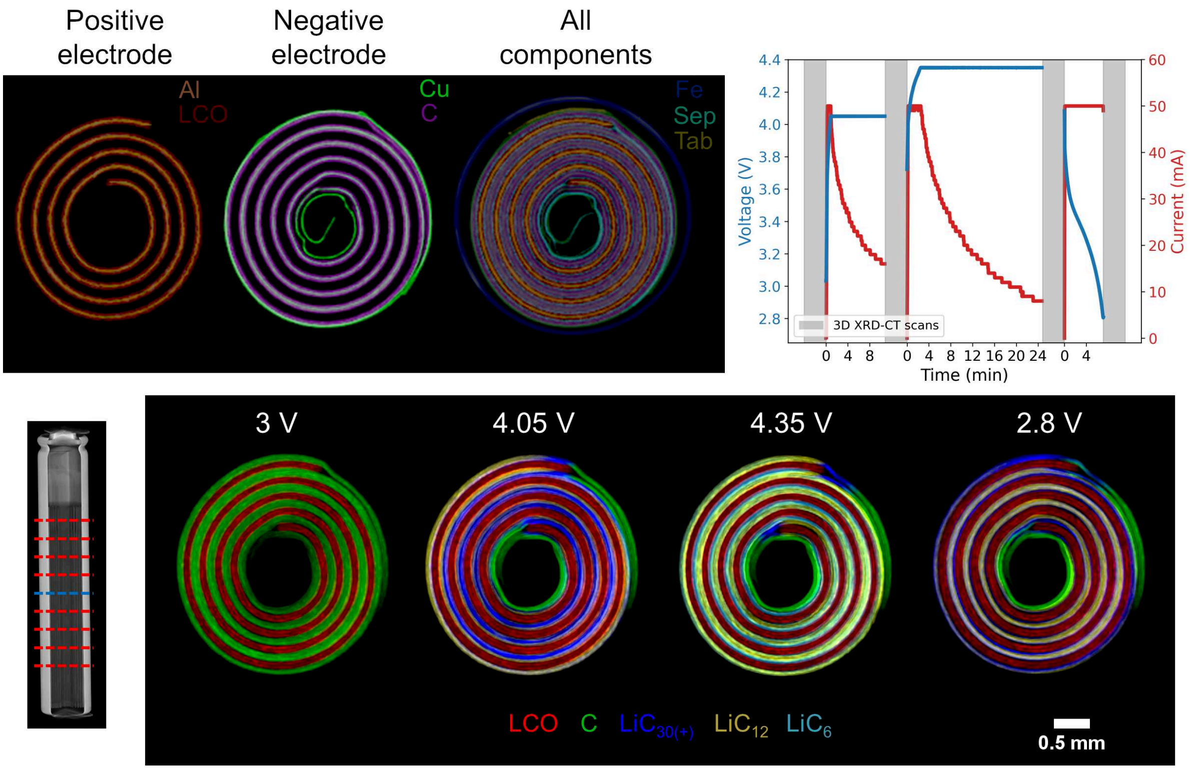

Figure 6: Operando 5D tomographic diffraction imaging (3D spatial + diffraction + time/potential) of a Panasonic CG-320A pintype Li-ion battery. The dataset enables simultaneous mapping of phase evolution and structural heterogeneity during cycling, demonstrating the unique value of XRD-CT for capturing crystallographic changes in working devices.

Education and training: a key aim of BIL is to be pedagogical. The datasets and accompanying notebooks can be embedded into undergraduate and postgraduate curricula, allowing students to interact with genuine experimental data rather than synthetic simulations. Exercises might include reconstructing tomographic volumes from raw radiographs, applying denoising filters to 2D diffraction patterns, or indexing EBSD patterns with both classical and machine learning approaches. For professional training, BIL offers a resource for workshops and summer schools, equipping early-career researchers with hands-on experience in handling multimodal imaging data. The ability to reproduce full pipelines, from raw data through to analysis, makes BIL uniquely suited for teaching reproducible research practices.

5 Outlook and Future Directions

The Battery Imaging Library sets a new standard for openness and reproducibility in battery imaging, but its true potential lies in growth and extension. Rather than a static dataset release, BIL is designed as an evolving platform that can adapt to the changing needs of the community and the rapid pace of imaging innovation.

FAIR-by-design: central to BIL's future is the website, which provides an intuitive entry point for discovering data. Its search and browse features make it straightforward to locate datasets by modality, length scale, device format, and chemistry, with clear signposting of raw versus processed data. By anchoring every dataset to a versioned DOI and supplying rich metadata, BIL aligns with FAIR principles so that data are findable, accessible, interoperable, and reusable.

Future contributions: although BIL already covers a wide range of modalities and chemistries, its structure allows for future additions. Researchers may extend the library to new materials systems, device types, or experimental environments, progressively broadening its scope. In this way, BIL can remain a relevant and useful reference resource as the field of battery imaging continues to expand.

AI development and benchmarks: the breadth of raw multimodal data in BIL is well suited to self-supervised learning, generative modelling, and the development of models that learn transferable representations across tasks and modalities which could underpin advances in reconstruction, segmentation, and multimodal data fusion.

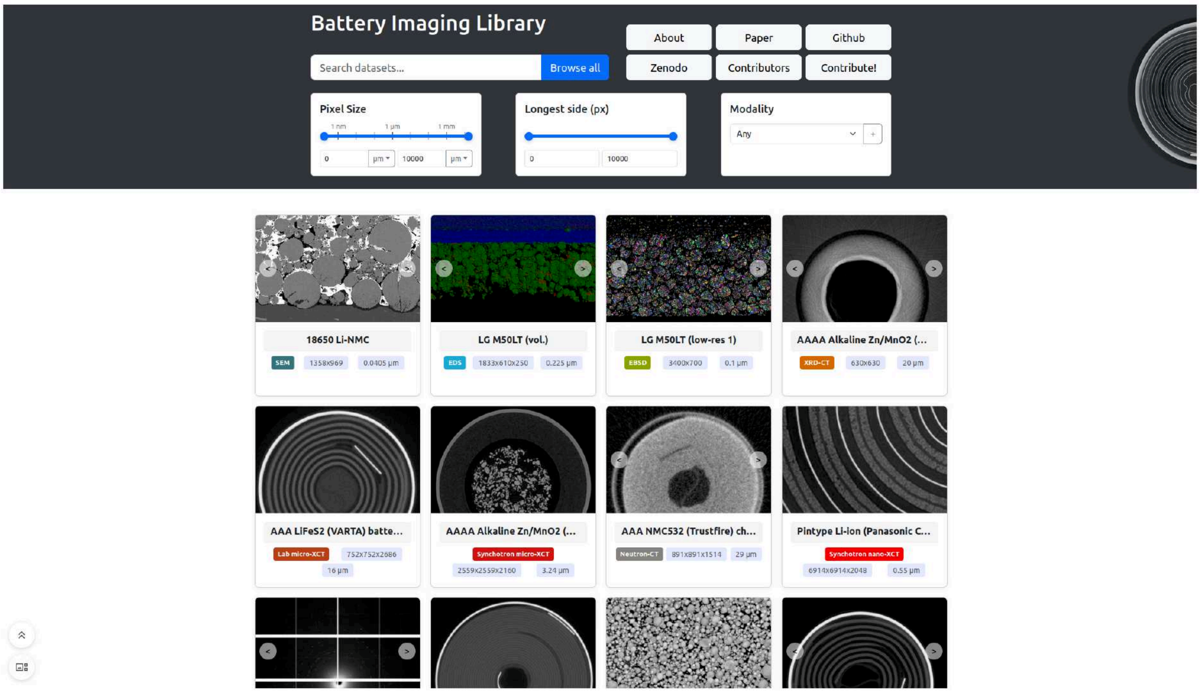

Figure 7: Screenshot of the Battery Imaging Library website interface. The tile-based design allows users to browse or search datasets by text, modality, or acquisition parameters (i.e image and voxel size). Each dataset page links directly to its Zenodo DOI.

Looking ahead, the Battery Imaging Library provides more than an archive: it is an infrastructure for reproducible research, computational innovation, and training. By combining a searchable website, FAIR-aligned publication practices, raw experimental multi-modal data, and the possibility of future dataset contributions from the community, BIL is positioned to become a valuable foundation for both current and emerging directions in battery imaging.

Code Availability

The Python notebooks used to handle the BIL data and for the website are provided through the BIL GitHub repository: `https://github.com/antonyvam/batteryimaginglibrary`.

Data Availability

The data presented or used in this work are accessible through `https://www.batteryimaginglibrary.com`.

Author Contributions

A.V. conceived the idea of BIL and led the experimental work. R.D. designed and developed the BIL website with feedback provided by A.V. and S.J.C, and performed post-processing of some data. The jupyter notebooks were created by A.V., E.P. and H.D. The X-ray micro-CT measurements at Imperial College London were performed by L.E.S.F. and A.V. The X-ray micro-CT measurements at the University of Southampton were performed by K.R., F.A.B. and A.V. The XRD-CT measurements at beamline P07 of DESY were performed by A.V., S.R., J.M. and A.D.B. O.G., A.C.D. and M.v.Z. were responsible for P07 instrumentation and setup at the PETRA III, DESY. The XRD-CT and X-ray micro-CT measurements at beamline I12 of Diamond Light Source were performed by A.V., S.R., J.M. and A.D.B. S.M., A.L., and G.B. were responsible for the I12 instrumentation and setup at the Diamond Light Source. D.M. prepared and provided the single particle and electrode NMC811 samples measured at the ESRF and DESY synchrotrons. The S3DXRD and X-ray nano-CT measurements at beamline ID11 of the ESRF were performed by A.V., S.R., J.M., P.O.A. and J.W. P.O.A. and J.W. were responsible for the ID11 instrumentation and setup at the ESRF. The neutron-CT measurements at the IMAT beamline of the ISIS Neutron and Muon Source were performed by W.K. and A.V.. W.K. was responsible for the IMAT instrumentation and setup at ISIS. The FIB-SEM/EDS/EBSD data acquired at the University of Manchester were provided by J.D.. The FIB-SEM/EDS/EBSD and X-ray nano-CT data acquired at the National Laboratory of the Rockies were provided by J.M., M.P. and D.P.F.. The FIB-SEM/EDS/EBSD acquired at the WMG were provided by

J.G., D.P. with funding secured by G.W. and L.F.J.P.. The nano-CT data acquired at EIL were provided by M.P.J., F.I., A.V.L. and R.J.. The 3D XANES-CT data acquired at SPring-8 were provided by Y.K., K.A. and O.S.. The TEM and APT data acquired at Imperial were provided by M.G.A., A.O., J.O.D., S.W., N.M. with funding secured by M.P.R, F.G. and S.C.. A.M.B., C.G., S.J.C., A.V. and S.D.M.J. secured funding for the creation of the BIL website by R.D. and for the experiments performed by S.R., J.M., A.D.B. and A.V.. A.V. performed the data curation and uploaded the BIL data to zenodo with contributions from R.D.. The manuscript was written by A.V. and R.D. with contributions and feedback given from all co-authors.

Acknowledgements

AV acknowledges funding through the Royal Society (IF\R2\222059) as a Royal Society Industry Fellow. RD acknowledges funding through the EPRSC and SFI Centre for Doctoral Training in Advanced Characterisation of Materials (EP/S023259/1). We acknowledge DESY (Hamburg, Germany), a member of the Helmholtz Association HGF, for the provision of experimental facilities. Parts of this research were carried out at PETRA III. Data was collected using beamline P07 operated/provided by DESY Photon Science. Beamtime was allocated for proposals I-20241139 EC and I-20231417. We acknowledge Diamond Light Source for time on Beamline I12 under Proposals MG36699 and MG38628. We acknowledge the European Synchrotron Radiation Facility (ESRF) for provision of synchrotron radiation facilities under proposal numbers ma6063 and ihhc3750. This work was supported by the National Research Facility for Lab X-ray CT (NXCT) through EPSRC grant EP/T02593X/1. WMG acknowledges support from High Value Manufacturing Catapult. The authors are grateful to the Henry Royce Institute for Advanced Materials, funded through EPSRC grants EP/R00661X/1, EP/S019367/1, EP/P025021/1 and EP/P025498/1. This work was authored by the Alliance for Sustainable Energy, LLC, the manager and operator of the National Laboratory of the Rockies for the US DOE. The views expressed in the article do not necessarily represent the views of the DOE or the US government. We acknowledge SPring-8 for time on Beamline BL37XU under Proposals 2024A1458 and 2024B1351.

Conflict of interest

The authors declare that they have no competing interests.

References

[1] Zhao Liu, Shuang Bai, et al. "FIB-SEM: Emerging Multimodal/Multiscale Characterization Techniques for Advanced Battery Development". In: *Chemical Reviews* 125.11 (2025), pp. 5228–5281. ISSN: 0009-2665. DOI: 10.1021/acs.chemrev.4c00831. URL: https://doi.org/10.1021/acs.chemrev.4c00831.

[2] A. P. Black, Andrea Sorrentino, et al. "Synchrotron radiation based operando characterization of battery materials". In: *Chem. Sci.* 14 (7 2023), pp. 1641–1665. DOI: 10.1039/D2SC04397A. URL: http://dx.doi.org/10.1039/D2SC04397A.

[3] R. F. Ziesche, Thomas M. M. Heenan, et al. "Multi-Dimensional Characterization of Battery Materials". In: *Advanced Energy Materials* 13.23 (2023), p. 2300103. DOI: https://doi.org/10.1002/aenm.202300103. URL: https://advanced.onlinelibrary.wiley.com/doi/abs/10.1002/aenm.202300103.

[4] Melissa Popeil, Francois L.E. Usseglio-Viretta, et al. "Heterogeneity of the Dominant Causes of Performance Loss in End-of-Life Cathodes and Their Consequences for Direct Recycling". In: *Advanced Energy Materials* 15.46 (2025), p. 2405371. DOI: https://doi.org/10.1002/aenm.202405371. eprint: https://advanced.onlinelibrary.wiley.com/doi/pdf/10.1002/aenm.202405371. URL: https://advanced.onlinelibrary.wiley.com/doi/abs/10.1002/aenm.202405371.

[5] Samuel J. Cooper, Scott A. Roberts, et al. "Methods—Kintsugi Imaging of Battery Electrodes: Distinguishing Pores from the Carbon Binder Domain using Pt Deposition". In: *Journal of The Electrochemical Society* 169.7 (July 2022), p. 070512. DOI: 10.1149/1945-7111/ac7a68. URL: https://dx.doi.org/10.1149/1945-7111/ac7a68.

[6] Farid Tariq, Vladimir Yufit, et al. "In-Operando X-ray Tomography Study of Lithiation Induced Delamination of Si Based Anodes for Lithium-Ion Batteries". In: *ECS Electrochemistry Letters* 3.7 (Jan. 2014), A76. DOI: 10.1149/2.0081407eel. URL: https://doi.org/10.1149/2.0081407eel.

[7] Donal P. Finegan, Antonis Vamvakeros, et al. "Spatial quantification of dynamic inter and intra particle crystallographic heterogeneities within lithium ion electrodes". In: *Nature Communications* 11.1 (Jan. 2020), p. 631. ISSN: 2041-1723. DOI: 10.1038/s41467-020-14467-x. URL: https://doi.org/10.1038/s41467-020-14467-x.

[8] Ralf F. Ziesche, Nikolay Kardjilov, et al. "Neutron imaging of lithium batteries". In: *Joule* 6.1 (2022), pp. 35–52. ISSN: 2542-4351. DOI: https://doi.org/10.1016/j.joule.2021.12.007. URL: https://www.sciencedirect.com/science/article/pii/S2542435121005766.

[9] F. De Carlo, Doğa Gürsoy, et al. "TomoBank: a tomographic data repository for computational x-ray science". In: *Measurement Science and Technology* 29.3 (Feb. 2018), p. 034004. DOI: 10.1088/1361-6501/aa9c19. URL: https://dx.doi.org/10.1088/1361-6501/aa9c19.

[10] Collaborative Computational Project in Tomographic Imaging (CCPi). *CCPi Tomographic Dataset Collection*. 2024. URL: https://ccpi.ac.uk/datasets/.

[11] Samuli Siltanen, Alexander Meaney, et al. *FIPS Open X-ray Tomographic Datasets*. Finnish Inverse Problems Society. 2022. URL: https://fips.fi/category/open-datasets/x-ray-tomographic-datasets/.

[12] The wwPDB Consortium. "EMDB—the Electron Microscopy Data Bank". In: *Nucleic Acids Research* 52.D1 (Nov. 2023), pp. D456–D465. ISSN: 0305-1048. DOI: 10.1093/nar/gkad1019. eprint: https://academic.oup.com/nar/article-pdf/52/D1/D456/55039450/gkad1019.pdf. URL: https://doi.org/10.1093/nar/gkad1019.

[13] Jeffrey M Ede. "Warwick electron microscopy datasets". In: *Machine Learning: Science and Technology* 1.4 (Sept. 2020), p. 045003. DOI: 10.1088/2632-2153/ab9c3c. URL: https://doi.org/10.1088/2632-2153/ab9c3c.

[14] Rossella Aversa, Mohammad Hadi Modarres, et al. "The first annotated set of scanning electron microscopy images for nanoscience". In: *Scientific Data* 5.1 (Aug. 2018), p. 180172. ISSN: 2052-4463. DOI: 10.1038/sdata.2018.172. URL: https://doi.org/10.1038/sdata.2018.172.

[15] Maximilian B. Kiss, Sophia B. Coban, et al. "2DeteCT - A large 2D expandable, trainable, experimental Computed Tomography dataset for machine learning". In: *Scientific Data* 10.1 (Sept. 2023), p. 576. ISSN: 2052-4463. DOI: 10.1038/s41597-023-02484-6. URL: https://doi.org/10.1038/s41597-023-02484-6.

[16] Johannes Leuschner, Maximilian Schmidt, et al. "LoDoPaB-CT, a benchmark dataset for low-dose computed tomography reconstruction". In: *Scientific Data* 8.1 (Apr. 2021), p. 109. ISSN: 2052-4463. DOI: 10.1038/s41597-021-00893-z. URL: https://doi.org/10.1038/s41597-021-00893-z.

[17] Henri Der Sarkissian, Felix Lucka, et al. "A cone-beam X-ray computed tomography data collection designed for machine learning". In: *Scientific Data* 6.1 (Oct. 2019), p. 215. ISSN: 2052-4463. DOI: 10.1038/s41597-019-0235-y. URL: https://doi.org/10.1038/s41597-019-0235-y.

[18] National Renewable Energy Laboratory. *Battery Microstructures Library*. Website. URL: https://www.nrel.gov/transportation/microstructure.

[19] A. Condon, B. Buscarino, et al. "A dataset of over one thousand computed tomography scans of battery cells". In: *Data in Brief* 55 (2024), p. 110614. ISSN: 2352-3409. DOI: https://doi.org/10.1016/j.dib.2024.110614. URL: https://www.sciencedirect.com/science/article/pii/S235234092400581X.

[20] M. D. Wilkinson, Michel Dumontier, et al. "The FAIR Guiding Principles for scientific data management and stewardship". In: *Scientific Data* 3.1 (2016), p. 160018. ISSN: 2052-4463. DOI: 10.1038/sdata.2016.18. URL: https://doi.org/10.1038/sdata.2016.18.

[21] A. Vamvakeros, D. Matras, et al. "Cycling Rate-Induced Spatially-Resolved Heterogeneities in Commercial Cylindrical Li-Ion Batteries". In: *Small Methods* 5.9 (2021), p. 2100512. ISSN: 2366-9608. DOI: 10.1002/smtd.202100512.

[22] D. Matras, T.E. Ashton, et al. "Emerging Chemical Heterogeneities in a Commercial 18650 NCA Li-ion Battery during Early Cycling Revealed by Synchrotron X-ray Diffraction Tomography". In: *Journal of Power Sources* 539 (2022), p. 231589. ISSN: 0378-7753. DOI: 10.1016/j.jpowsour.2022.231589.

[23] Melissa Popeil, Francois L.E. Usseglio-Viretta, et al. "Heterogeneity of the Dominant Causes of Performance Loss in End-of-Life Cathodes and Their Consequences for Direct Recycling". In: *Advanced Energy Materials* 15.46 (2025), p. 2405371. doi: https://doi.org/10.1002/aenm.202405371. eprint: https://advanced.onlinelibrary.wiley.com/doi/pdf/10.1002/aenm.202405371. url: https://advanced.onlinelibrary.wiley.com/doi/abs/10.1002/aenm.202405371.

[24] Orkun Furat, Donal P. Finegan, et al. "Quantifying the Impact of Charge Rate and Number of Cycles on Structural Degeneration of Li-Ion Battery Electrodes". In: *Journal of The Electrochemical Society* 169.10 (Oct. 2022), p. 100541. doi: 10.1149/1945-7111/ac99a1. url: https://doi.org/10.1149/1945-7111/ac99a1.

[25] Neil Mulcahy, Syeda Ramin Jannat, et al. *Degradation and SEI Evolution in Alloy Anodes Revealed by Correlative Liquid-Cell Electrochemistry and Cryogenic Microscopy*. 2025. arXiv: 2505.21434 [cond-mat.mtrl-sci]. url: https://arxiv.org/abs/2505.21434.

[26] Neil Mulcahy, James O. Douglas, et al. *A Workflow for Correlative in-situ Nano-chip Liquid Cell Transmission Electron Microscopy and Atom Probe Tomography Enabled by Cryogenic Plasma Focused Ion Beam*. 2025. arXiv: 2504.19020 [cond-mat.mtrl-sci]. url: https://arxiv.org/abs/2504.19020.

[27] A. Vamvakeros, S. D. M. Jacques, et al. "5D Operando Tomographic Diffraction Imaging of a Catalyst Bed". In: *Nature Communications* 9.1 (2018), p. 4751. issn: 2041-1723. doi: 10.1038/s41467-018-07046-8.

[28] D. Matras, A. Vamvakeros, et al. "Multi-Length Scale 5D Diffraction Imaging of Ni–Pd/CeO2–ZrO2/Al2O3 Catalyst during Partial Oxidation of Methane". In: *Journal of Materials Chemistry A* 9.18 (2021), pp. 11331–11346. issn: 2050-7488. doi: 10.1039/D1TA01464A.

[29] J. Sottmann, Amund Ruud, et al. "5D total scattering computed tomography reveals the full reaction mechanism of a bismuth vanadate lithium ion battery anode". In: *Phys. Chem. Chem. Phys.* 24 (44 2022), pp. 27075–27085. doi: 10.1039/D2CP03892G. url: http://dx.doi.org/10.1039/D2CP03892G.

[30] Amir Dahari, Steve Kench, et al. "Fusion of Complementary 2D and 3D Mesostructural Datasets Using Generative Adversarial Networks". In: *Advanced Energy Materials* 13.2 (2023), p. 2202407. doi: https://doi.org/10.1002/aenm.202202407. eprint: https://advanced.onlinelibrary.wiley.com/doi/pdf/10.1002/aenm.202202407. url: https://advanced.onlinelibrary.wiley.com/doi/abs/10.1002/aenm.202202407.

[31] J. S. Jørgensen, E. Ametova, et al. "Core Imaging Library - Part I: a versatile Python framework for tomographic imaging". In: *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 379.2199 (2021), p. 20200192. doi: 10.1098/rsta.2020.0192. url: https://doi.org/10.1098/rsta.2020.0192.

[32] E. Papoutsellis, E. Ametova, et al. "Core Imaging Library - Part II: multichannel reconstruction for dynamic and spectral tomography". In: *Philos Trans A Math Phys Eng Sci* 379.2204 (July 2021), p. 20200193. doi: 10.1098/rsta.2020.0193. url: https://doi.org/10.1098/rsta.2020.0193.

[33] A. Vamvakeros, E. Papoutsellis, et al. "nDTomo: a modular Python toolkit for X-ray chemical imaging and tomography". In: *Digital Discovery* 4 (9 2025), pp. 2579–2592. doi: 10.1039/D5DD00252D. url: http://dx.doi.org/10.1039/D5DD00252D.

[34] W. van Aarle, W. J. Palenstijn, et al. "The ASTRA Toolbox: A platform for advanced algorithm development in electron tomography". In: *Ultramicroscopy* 157 (2015), pp. 35–47. issn: 0304-3991. doi: https://doi.org/10.1016/j.ultramic.2015.05.002. url: https://www.sciencedirect.com/science/article/pii/S0304399115001060.

[35] A. Vamvakeros, D. Matras, et al. "Real-Time Tomographic Diffraction Imaging of Catalytic Membrane Reactors for the Oxidative Coupling of Methane". In: *Catalysis Today* 364 (2021), pp. 242–255. issn: 0920-5861. doi: 10.1016/j.cattod.2020.05.045.

[36] A. Vamvakeros, A. A. Coelho, et al. "DLSR: A Solution to the Parallax Artefact in X-ray Diffraction Computed Tomography Data". In: *Journal of Applied Crystallography* 53.6 (2020), pp. 1531–1541. doi: 10.1107/S1600576720013576.

[37] H. Dong, S. D. M. Jacques, et al. "Obtaining Parallax-Free X-ray Powder Diffraction Computed Tomography Data with a Self-Supervised Neural Network". In: *npj Computational Materials* 10.1 (2024), p. 201. issn: 2057-3960. doi: 10.1038/s41524-024-01389-1.