1 Benchmark Overview Table

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|--|---|----------------------------------|---|---|----------------|---|-------------------------------|--|--------------|
| jet Classification dataset specification metric specification metric specification dataset specification datas | Jet Classification | Particle Physics | Real-time classifi- cation of particle jets using HL-LHC simulation features | classification, real-time ML, jet tagging, QKeras | Classification | Real-time inference, model compression performance | Accuracy, AUC | Keras DNN, QKeras quantized DNN | [1]⇒ |
| regular Sensor Data Compression datasata Specification metric Solution damentation | Irregular Sensor Data Compression | Particle Physics | Real-time compression of sparse sensor data with autoencoders | compression, autoencoder, sparse data, irregular sampling | Compression | Reconstruction quality, com- pression effi- ciency | MSE, Compression ratio | Autoencoder Quantized autoen- coder | , [2]⇒ |
| Beam Control datases specification metrics specification metrics specification specifi | Beam Control | Accelerators and Mag- nets | Reinforcement learning control of accelera- tor beam position | nt RL, beam stabilization, control systems, simulation | Control | Policy performance in simulated accelerator control | Stability, Control loss | DDPG, PPO (planned) | [2], [3]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|--|---|----------------------------------|---|--|---|--|--|--|----------|
| Ultrafact jet classification at the HL-LHC dataset control of the | Ultrafast jet classifica- tion at the HL-LHC | Particle Physics | FPGA- optimized real-time jet origin classifica- tion at the HL-LHC | jet classification, FPGA, quantization-aware training, Deep Sets, Interaction Networks | Classification | Real-time inference under FPGA constraints | Accuracy, Latency, Resource utilization | MLP, Deep Sets, Inter- action Net- work | [4]⇒ |
| Quench detection datasas Tipo (fication metric Station datasas reference Station datas reference Station datasas reference Station datasas reference Station datasas reference Station datasas reference Station datas reference Station datas reference Station datas reference Stati | Quench de- tection | Accelerators and Mag- nets | Real-time detection of super- conducting magnet quenches using ML | quench detection, autoencoder, anomaly detection, real-time | Anomaly detection, Quench localization | Real-time anomaly de- tection with multi-modal sensors | ROC- AUC, Detection latency | Autoencoder, RL agents (in devel- opment) | |
| datasa Tradicalion metricalion selevi | DUNE | Particle Physics | Real-time ML for DUNE DAQ time-series data | DUNE, time-series, real-time, trigger | Trigger selection, Timeseries anomaly detection | Low-latency event detection | Detection efficiency, Latency | CNN, LSTM (planned) | [5]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|--|--|---|---|---|--|---|---|---|----------|
| Intelligent experiments through real-time datases through resident data | Intelligent experiments through real-time AI | Instrumentat and De- tectors; Nuclear Physics; Particle Physics | ioReal-time FPGA- based trigger- ing and detector control for sPHENIX and future EIC | FPGA, Graph Neural Network, hls4ml, real- time infer- ence, detector control | Trigger classification, Detector control, Realtime inference | Low-latency GNN inference on FPGA | Accuracy (charm and beauty detection), Latency (micros), Resource utilization (LUT/FF/B | Bipartite Graph Net- work with Set Trans- formers (BGN-ST), GarNet (edge- RAMSSIESP)) | [6]⇒ |
| Neural Architecture Codesign for frait Physics Application and the second secon | Neural Ar- chitecture Codesign for Fast Physics Applications | Physics; Materials Science; Particle Physics | Automated neural ar- chitecture search and hardware- efficient model codesign for fast physics ap- plications | neural ar- chitecture search, FPGA de- ployment, quantization, pruning, hls4ml | Classification, Peak finding | Hardware- aware model optimization; low-latency inference | Accuracy, Latency, Resource utilization | NAC- based BraggNN, NAC- optimized Deep Sets (jet) | [7]⇒ |
| Smart Pixels for LHC dataset Pixels fination metr reference Skillen_governmentation | Smart Pixels for LHC | Particle Physics; Instrumen- tation and Detectors | On-sensor, in-pixel ML fil- tering for high-rate LHC pixel detectors | smart pixel, on-sensor in- ference, data reduction, trigger | Image Classi- fication, Data filtering | On-chip, low-power inference; data reduction | Data rejection rate, Power per pixel | 2-layer pixel NN | [8]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|--|---|---------------------|--|--|---|---|--|------------------------|----------|
| HEDM (Braggill) datasa Bragilla (Braggill) metrica data data data data data data data da | HEDM (BraggNN) | Material Science | Fast Bragg peak anal- ysis using deep learn- ing in diffraction microscopy | BraggNN, diffraction, peak finding, HEDM | Peak detection | High- throughput peak localiza- tion | Localization accuracy, Inference time | ${ m BraggNN}$ | [9]⇒ |
| do STEM datases specification metric solution downless and metric solution | 4D-STEM | Material Science | Real-time ML for scanning trans- mission electron microscopy | 4D-STEM, electron mi- croscopy, real-time, image pro- cessing | Image Classification, Streamed data inference | Real-time large- scale microscopy inference | Classification accuracy, Through- put | CNN models (prototype) | [10]⇒ |
| in-Situ High-Speed Computer Vision datases registration methyl services and second methyl seco | In-Situ High- Speed Com- puter Vision | Fusion/Plasr | naReal-time image clas- sification for in-situ plasma diagnostics | plasma, insitu vision, real-time ML | Image Classification | Real-time diag- nostic inference | Accuracy, FPS | CNN | [11]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|---|-----------------------------------|--|---|---|---|--|--|---|----------|
| BenchGuncil AlBench dataset BenchGabon metron benchmarken dataset BenchGabon metron benchmarken dataset BenchGabon reference sekulon dataset BenchGabon | BenchCouncil AIBench | General | End-to-end AI bench- marking across micro, compo- nent, and application levels | benchmarking, AI systems, application- level evalua- tion | Training, Inference, Endto-end AI workloads | System-level AI workload perfor- mance | Throughput, Latency, Accuracy | ResNet, BERT, GANs, Recom- mendation systems | [12]⇒ |
| Bench Council BigData Bench dataset The fire aton metroe solution governmentation | BenchCouncil Big- DataBench | General | Big data and AI bench- marking across structured, semi- structured, and un- structured data work- loads | big data, AI benchmark- ing, data analytics | Data pre- processing, Inference, End- to-end data pipelines | Data processing and AI model inference perfor- mance at scale | Data through- put, La- tency, Accuracy | CNN, LSTM, SVM, XGBoost | [13]⇒ |
| MLPerf HPC datasation metric metric solution goodmentation | ** MLPerf HPC | Cosmology, Climate, Protein Structure, Catalysis | Scientific ML training and inference on HPC systems | HPC, training, inference, scientific ML | Training, Inference | Scaling efficiency, training time, model accuracy on HPC | Training time, Accuracy, GPU utilization | CosmoFlow, DeepCAM, OpenCata- lyst | [14]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|---|-------------------------------|---|--|--|---|---|---|---|----------|
| MLCommons Science datases metric reference seaton decementation | MLCommons Science | Earthquake, Satellite Image, Drug Discovery, Electron Microscope, CFD | AI benchmarks for scientific applications including time-series, imaging, and simulation | science AI, benchmark, MLCom- mons, HPC | Time-series analysis, Image classification, Simulation sur- rogate modeling | Inference accuracy, simulation speed-up, generalization | MAE, Accuracy, Speedup vs simulation | CNN, GNN, Trans- former | [15]⇒ |
| LHC New Physics Dataset dataset and Circation metrics and Circation | LHC New Physics Dataset | Particle Physics; Real-time Triggering | Real-time LHC event filtering for anomaly detec- tion using proton collision data | anomaly detection, proton collision, real-time inference, event filtering, unsupervised ML | Anomaly detection, Event classification | Unsupervised signal detection under latency and bandwidth constraints | ROC- AUC, Detection efficiency | Autoencoder, Variational autoen- coder, Isolation forest | [16]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|--|-------------------------|--|---|--|--|---|---|---|----------|
| M.Commons Medical Al datases specification metrics shadio appendication metrics shadio appendication specification specification specification shadio appendication specification specif | MLCommons Medical AI | Healthcare; Medical AI | Federated bench-marking and evaluation of medical AI models across diverse real-world clinical data | medical AI, federated evaluation, privacy-preserving, fairness, healthcare benchmarks | Federated evaluation, Model validation | Clinical accuracy, fairness, generalizability, privacy compliance | ROC AUC, Accuracy, Fairness metrics | MedPerf- validated CNNs, GaNDLF workflows | [17]⇒ |
| CaloChallenge 2022 datasas Procification metric opportunities of the control of the control opportunities of the control opportuniti | CaloChallenge 2022 | LHC Calorime- ter; Parti- cle Physics | Fast generative- model- based calorimeter shower simulation evaluation | calorimeter simulation, generative models, surrogate modeling, LHC, fast simulation | Surrogate modeling | Simulation fi- delity, speed, efficiency | Histogram similarity, Classifier AUC, Gen- eration latency | VAE variants, GAN variants, Normalizing flows, Diffusion models | [18]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|---|--|-------------------------------|--|---|---|---|--|--------------------------------|----------|
| Papers With Code (SOTA Platform) datasel The Pication metric Solution downfertation | Papers With Code (SOTA Platform) | General ML; All domains | Open platform tracking state-of- the-art results, bench- marks, and implemen- tations across ML tasks and papers | leaderboard, benchmark- ing, repro- ducibility, open-source | Multiple (Classification, Detection, NLP, etc.) | Model performance across tasks (accuracy, F1, BLEU, etc.) | Task-specific (Accuracy, F1, BLEU, etc.) | All published models with code | [19]⇒ |
| Codabench datasas metres reference seution accementation | . Codabench | General ML; Multi- ple | Opensource platform for organizing reproducible AI benchmarks and competitions | benchmark platform, code sub- mission, competi- tions, meta- benchmark | Multiple | Model reproducibility, performance across datasets | Submission count, Leader- board ranking, Task- specific metrics | Arbitrary code submissions | [20]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|---|-------------------|--|---|--|---------------------------|---|---|---|----------|
| Sabath (SBI-FAIR) dataset The (PicaSon metric Salution downfentation | Sabath (SBI-FAIR) | Systems; Metadata | FAIR metadata frame- work for ML-driven surrogate workflows in HPC systems | meta- benchmark, metadata, HPC, surro- gate modeling | Systems bench- marking | Metadata tracking, repro- ducible HPC workflows | Metadata complete- ness, FAIR compliance | N/A | [21]⇒ |
| PDEBench dolassa Specification metrics reference Solution Gasementation | PDEBench | CFD; Weather Modeling | Benchmark suite for ML-based surrogates solving time- dependent PDEs | PDEs, CFD, scientific ML, surrogate modeling, NeurIPS | Supervised Learning | Time-dependent PDE model- ing; physical accuracy | RMSE, boundary RMSE, Fourier RMSE | FNO, U- Net, PINN, Gradient- Based inverse methods | [22]⇒ |
| metre Sudden gosementation | The Well | biological systems, fluid dy- namics, acoustic scattering, astro- physical MHD | Foundation model + surrogate dataset spanning 16 physical simulation domains | surrogate modeling, founda- tion model, physics sim- ulations, spatiotempo- ral dynamics | Supervised Learning | Surrogate modeling, physics-based prediction | Dataset size, Do- main breadth | FNO baselines, U-Net baselines | [23]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|--|--|---------------------|---|--|-----------------------------|--|--|---|----------|
| metrics search dataset security and metrics search dataset security and metrics search dataset security and metrics search dataset search dat | LLM- Inference- Bench | LLM; HPC/inferen | Hardware ceperfor- mance bench- marking of LLMs on AI acceler- ators | LLM, inference benchmarking, GPU, accelerator, throughput | Inference Bench- marking | Inference throughput, latency, hard- ware utilization | Token throughput (tok/s), Latency, Framework- hardware mix perfor- mance | LLaMA- 2-7B, LLaMA- 2-70B, Mistral-7B, Qwen-7B | [24]⇒ |
| SCLang framework datasas methys reference skilden spalmentation | SGLang Framework | LLM Vision | Fast serving framework for LLMs and visionlanguage models | LLM serving, vision-language, RadixAttention, performance, JSON decoding | Model serving framework | Serving throughput, JSON/task- specific latency | Tokens/sec, Time-to- first-token, Through- put gain vs baseline | LLaVA, DeepSeek, Llama | [25]⇒ |
| vLLM Inference and Serving Engine datases specification metric datases specification order reference shadon against attaining the specification of the specification of the specification of the specification of the specific | vLLM In- ference and Serving En- gine | LLM; HPC/inferen | High- cethroughput, memory- efficient inference and serving engine for LLMs | LLM inference, PagedAttention, CUDA graph, streaming API, quantization | Inference Bench- marking | Throughput, latency, memory efficiency | Tokens/sec, Time to First Token (TTFT), Memory footprint | LLaMA, Mixtral, FlashAttentic based models | |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|---|--------------------------------------|--|---|--|---------------------------|--|---|-------------------------------------|----------|
| vLLM Performance Dashboard dataset Topografion metries Solution desertions | vLLM Perfor- mance Dash- board | LLM; HPC/inferen | Interactive cedashboard showing inference performance of vLLM | Dashboard, Throughput visualization, Latency anal- ysis, Metric tracking | Performance visualization | Throughput, latency, hardware utilization | Tokens/sec, TTFT, Memory usage | LLaMA-2, Mistral, Qwen | [27]⇒ |
| Nixta ReuralForcast datases Trocification metric advantage of the control of the | Nixtla Neu- ralForecast | Time- series fore- casting; General ML | High-performance neural fore-casting library with >30 models | time-series, neural fore- casting, NBEATS, NHITS, TFT, probabilistic forecasting, usability | Time-series fore-casting | Forecast accuracy, interpretability, speed | RMSE, MAPE, CRPS | NBEATS, NHITS, TFT, DeepAR | [28]⇒ |
| Nixta Neural Forecast NHTS dataset Specification metric specification metric specification generation | Nixtla Neu- ral Forecast NHITS | Time- series; General ML | Official NHITS imple- mentation for long- horizon time series forecasting | NHITS, long-horizon forecasting, neural in- terpolation, time-series | Time-series fore-casting | Accuracy, compute efficiency for long series | RMSE, MAPE | NHITS | [29]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|---|--|-----------------------------------|---|--|---|---|--|--|----------|
| Nixta Neural Forecast TimeLLM datases concentration metric services accommendation | Nixtla Neu- ral Forecast TimeLLM | Time- series; General ML | Reprogramm LLMs for time series forecasting | ingime-LLM, language model, time- series, repro- gramming | Time-series fore-casting | Model reuse via LLM, few-shot forecasting | RMSE, MAPE | Time-LLM | [30]⇒ |
| Nixta Neural Forecast TimeGFT datases metric reference Salation disantentation | Nixtla Neu- ral Forecast TimeGPT | Time- series; General ML | Time-series founda- tion model "TimeGPT" for fore- casting and anomaly detection | TimeGPT, founda- tion model, time-series, generative model | Time-series forecasting, Anomaly detec- tion | Zero-shot forecasting, anomaly detec- tion | RMSE, Anomaly detection metrics | TimeGPT | [31]⇒ |
| HOR ML Ancerely Challenge (Gravitational Washington) and the state of | HDR ML Anomaly Challenge (Gravita- tional Waves) | Astrophysics: Time-series | Detecting anomalous gravitational- wave sig- nals from LIGO/Virgo datasets | anomaly detection, gravitational waves, as- trophysics, time-series | Anomaly detection | Novel event detection in physical signals | ROC- AUC, Preci- sion/Recall | Deep latent CNNs, Au- toencoders | [32]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|---|---|---|---|--|-------------------|---|---|-------------------------------------|----------|
| HDR ML Anomaly Challenge (Butterfly) dataset fination metries fination reference session documentation | HDR ML Anomaly Challenge (Butterfly) | Genomics; Image/CV | Detecting hybrid butterflies via image anomaly detection in genomic- informed dataset | anomaly detection, computer vision, genomics, butterfly hybrids | Anomaly detection | Hybrid detection in biological systems | Classification accuracy, F1 score | CNN- based detectors | [32]⇒ |
| HDR Mt. Anomaly Challenge (See Level Ris | HDR ML Anomaly Challenge (Sea Level Rise) | Climate Science; Time- series, Image/CV | Detecting anomalous sea-level rise and flooding events via timeseries and satellite imagery | anomaly detection, climate sci- ence, sea-level rise, time- series, remote sensing | Anomaly detection | Detection of environmental anomalies | ROC- AUC, Preci- sion/Recall | CNNs, RNNs, Transform- ers | [32]⇒ |
| Single Qubit Readout on QICK System dataset The (Fication dataset The Control of | Single Qubit Readout on QICK System | Quantum Computing | Real-time single- qubit state classifica- tion using FPGA firmware | qubit read- out, hls4ml, FPGA, QICK | Classification | Single-shot fi- delity, inference latency | Accuracy, Latency | hls4ml quantized NN | [33]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|--|---|---|--|--|---|--|---|---|----------|
| GOA A Gradual Lord Goaph Word Continue and Joseph Barrier Benthing | GPQA: A Graduate- Level Google- Proof Ques- tion and Answer Benchmark | Science (Biology, Physics, Chemistry) | Graduate-level, expert- validated multiple- choice questions hard even with web access | Google-proof, multiple- choice, expert reasoning, science QA | Multiple choice | Scientific reasoning, knowledge probing | Accuracy | GPT-4 baseline | [34]⇒ |
| SeafloorAl datassal The (Fication datas)) and (Fication datas) an | SeafloorAI | Marine Science; Vision- Language | Large-scale vision-language dataset for seafloor mapping and geological classification | sonar imagery, vision- language, seafloor mapping, segmentation, QA | Image segmentation, Visionlanguage QA | Geospatial understanding, multimodal reasoning | Segmentation pixel accu- racy, QA accuracy | SegFormer, ViLT-style multi- modal models | [35]⇒ |
| SuperCon3D dataset methor reference Skulion downerstation | SuperCon3D | Materials Science; Supercon- ductivity | Dataset and models for predict- ing and generating high-Tc supercon- ductors using 3D crystal structures | superconductiv crystal struc- tures, equiv- ariant GNN, generative models | ityRegression (Tc prediction), Generative modeling | Structure-to- property predic- tion, structure generation | MAE (Tc), Validity of generated structures | SODNet, DiffCSP- SC | [36]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|--|--------------------------------|--|--|--|---|--|--|--|----------|
| GeSS datasas mattre reference 3044to _ gsortlentation | GeSS | Scientific ML; Ge- ometric Deep Learning | Benchmark suite eval- uating geometric deep learn- ing models under real-world distribu- tion shifts | geometric deep learning, distribution shift, OOD robustness, scientific applications | Classification, Regression | OOD performance in scientific settings | Accuracy, RMSE, OOD ro- bustness delta | GCN, EGNN, DimeNet++ | [37]⇒ |
| Vocal Call Locator (VCL) datasia profilestion metries selection accommendation | Vocal Call Locator (VCL) | Neuroscience Bioacous- tics | ; Benchmarkin sound-source localization of rodent vocalizations from multichannel audio | g source lo- calization, bioacoustics, time-series, SSL | Sound source localization | Source localization accuracy in bioacoustic settings | Localization error (cm), Re- call/Precision | CNN- based SSL models | [38]⇒ |
| MassSpecGym dataset metre me | MassSpecGym | Cheminforma Molecular Discovery | atiBenchmark suite for discovery and identi- fication of molecules via MS/MS | mass spectrometry, molecular structure, de novo generation, retrieval, dataset | De novo generation, Retrieval, Simulation | Molecular identification and generation from spectral data | Structure accuracy, Retrieval precision, Simulation MSE | Graph- based generative models, Retrieval baselines | [39]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|--|---------------------------|---|--|--|-------------------------------|--|--|--|----------|
| Urban Data Layer (UDL) dataset Transfer (It alion metries to the section of the | Urban Data Layer (UDL) | Urban Comput- ing; Data Engineer- ing | Unified data pipeline for multi- modal urban science research | data pipeline, urban science, multi-modal, benchmark | Prediction, Classification | Multi-modal urban inference, standardization | Task- specific accuracy or RMSE | Baseline regres- sion/classifica pipelines | [40]⇒ |
| Delta Squared DFT datasal Tracelle ation matries software assertion assertio | Delta Squared- DFT | Computation Chemistry; Materials Science | alBenchmarkin machine- learning corrections to DFT using Delta Squared- trained models for reaction energies | g density functional theory, Delta Squared-ML correction, reaction energetics, quantum chemistry | Regression | High-accuracy energy pre- diction, DFT correction | Mean Absolute Error (eV), Energy ranking accuracy | Delta Squared- ML correction networks, Kernel ridge regression | [41]⇒ |
| LLMs for Crop Science datassa Specification metrics school assembly separation reference Solution assembly assembly separation | LLMs for Crop Science | Agricultural Science; NLP | Evaluating LLMs on crop trait QA and textual inference tasks with domain- specific prompts | crop science, prompt engineering, domain adaptation, question answering | Question Answering, Inference | Scientific knowledge, crop reasoning | Accuracy, F1 score | GPT-4, LLaMA- 2-13B, T5-XXL | [42]⇒ |

| Ratings | Name | Domain | Focus | Keywords | Task Types | AI Capability | Metrics | Models | Citation |
|--|----------------|---|--|--|---------------|---|-----------------------|--|----------|
| SPIGA (LLM) datasas The fireation metric for a section fo | SPIQA (LLM) | Multimodal Scientific QA; Com- puter Vision | Evaluating LLMs on image- based scientific paper figure QA tasks (LLM Adapter perfor- mance) | multimodal QA, scientific figures, image+text, chain-of- thought prompting | Multimodal QA | Visual reasoning, scientific figure understanding | Accuracy, F1 score | LLaVA, MiniGPT- 4, Owl- LLM adapter variants | [43]⇒ |

2 Radar Chart Table

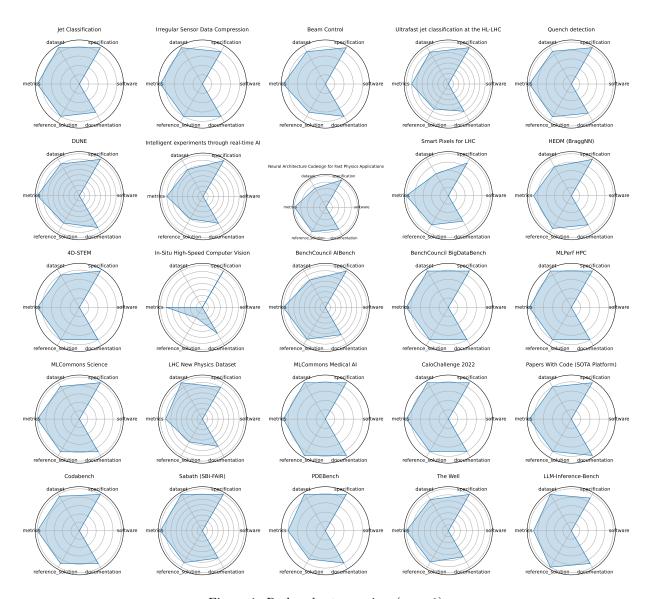


Figure 1: Radar chart overview (page 1)

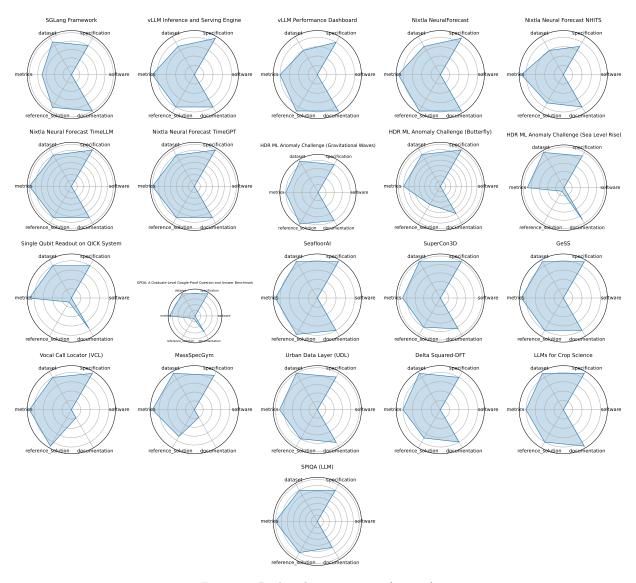


Figure 2: Radar chart overview (page 2)

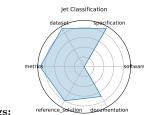
3 Benchmark Details

4 Jet Classification

date: 2024-05-01 last updated: 2024-05 expired: unkown valid: yes url: https://github.com/fastmachinelearning/fastml-science/tree/main/jet-classify domain: Particle Physics focus: Real-time classification of particle jets using HL-LHC simulation features keywords: - classification - real-time ML - jet tagging - QKeras task types: - Classification ai capability measured: - Real-time inference - model compression performance metrics: - Accuracy - AUC models: - Keras DNN - QKeras quantized DNN ml motif: - Real-time type: Benchmark ml task: Supervised Learning notes: Includes both float and quantized models using QKeras contact.name: Jules Muhizi contact.email: unkown dataset.name: JetClass dataset.url: https://zenodo.org/record/6619768 results.name: ChatGPT LLM $\textbf{results.url:} \quad \text{https://docs.google.com/document/d/1runrcij-eoH3} \quad \text{lgGZ8wm2z1YbL1Qf5cSNbVbHyWFDs4} \\ \text{formula} \quad \text{lgGZ8wm2z1$ fair.reproducible: True fair.benchmark ready: True ratings.software.rating: 0 ratings.software.reason: Not analyzed. ratings.specification.rating: 9.0 ratings.specification.reason: Task and format (multiple-choice QA with 5 options) are clearly defined; grounded in ConceptNet with consistent structure, though no hardware/system constraints are specified. ratings.dataset.rating: 9.0 ratings.dataset.reason: Public, versioned, and FAIR-compliant; includes metadata, splits, and licensing; well-integrated with HuggingFace and other ML libraries. ratings.metrics.rating: 9.0 ratings.metrics.reason: Accuracy is a simple, reproducible metric aligned with task goals; no ambiguity in evaluation. ratings.reference solution.rating: 8.0 ratings.reference solution.reason: Several baseline models (e.g., BERT, RoBERTa) are reported with scores; implementations exist in public repos, but not bundled as an official starter kit. ratings.documentation.rating: 7.0 ratings.documentation.reason: Clear paper, GitHub repo, and integration with HuggingFace Datasets; full reproducibility

id: jet_classificationCitations: [1]

requires manually connecting models to dataset.



5 Irregular Sensor Data Compression

date: 2024-05-01

last updated: 2024-05

expired: unkown

valid: yes

url: https://github.com/fastmachinelearning/fastml-science/tree/main/sensor-data-compression

domain: Particle Physics

focus: Real-time compression of sparse sensor data with autoencoders **keywords:** - compression - autoencoder - sparse data - irregular sampling

task types: - Compression

ai capability measured: - Reconstruction quality - compression efficiency

 $\mathbf{metrics:}\ \ \text{-}\ \mathrm{MSE}\ \text{-}\ \mathrm{Compression}\ \mathrm{ratio}$

models: - Autoencoder - Quantized autoencoder

ml motif: - Real-time, Image/CV

type: Benchmark

ml task: Unsupervised Learning

notes: Based on synthetic but realistic physics sensor data

contact.name: Ben Hawks, Nhan Tran

contact.email: unkown

dataset.name: Custom synthetic irregular sensor dataset

dataset.url: see GitHub repo results.name: ChatGPT LLM fair.reproducible: True fair.benchmark_ready: True ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 8.0

ratings.specification.reason: Classification is clearly defined for real-time inference on simulated LHC jets. Input features (HLFs) are documented, though exact latency or resource constraints are not numerically specified.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Two datasets (OpenML and Zenodo) are public, well-formatted, and documented; FAIR principles are followed, though richer metadata would raise confidence to a 10.

ratings.metrics.rating: 9.0

ratings.metrics.reason: AUC and Accuracy are standard, quantitative, and well-aligned with goals of jet tagging and inference efficiency.

ratings.reference solution.rating: 8.0

ratings.reference_solution.reason: Float and quantized Keras/QKeras models are provided with results. Reproducibility is good, though full automation and documentation could be improved.

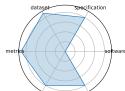
ratings.documentation.rating: 8.0

ratings.documentation.reason: GitHub contains baseline code, data loaders, and references, but setup for deployment (e.g., FPGA pipeline) requires familiarity with the tooling.

id: irregular_sensor_data_compression

Citations: [2]

Irregular Sensor Data Compression



6 Beam Control

date: 2024-05-01

last updated: 2024-05

expired: unkown

valid: yes

url: https://github.com/fastmachinelearning/fastml-science/tree/main/beam-control

domain: Accelerators and Magnets

focus: Reinforcement learning control of accelerator beam position keywords: - RL - beam stabilization - control systems - simulation

task types: - Control

ai capability measured: - Policy performance in simulated accelerator control

metrics: - Stability - Control lossmodels: - DDPG - PPO (planned)ml motif: - Real-time, RL

type: Benchmark

ml task: Reinforcement Learning

notes: Environment defined, baseline RL implementation is in progress

contact.name: Ben Hawks, Nhan Tran

contact.email: unkown
results.name: ChatGPT LLM
fair.reproducible: in progress
fair.benchmark_ready: in progress

ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9.0

ratings.specification.reason: Task is well defined (real-time compression of sparse, irregular sensor data using autoencoders); latency constraints are implied but not fully quantified.

ratings.dataset.rating: 8.0

ratings.dataset.reason: Dataset is custom and synthetic but described well; FAIR-compliance is partial (reusable and accessible, but not externally versioned with rich metadata).

ratings.metrics.rating: 9.0

ratings.metrics.reason: Uses standard quantitative metrics (MSE, compression ratio) clearly aligned with compression and reconstruction goals.

ratings.reference_solution.rating: 7.0

ratings.reference solution.reason: Baseline (autoencoder and quantized variant) is provided, but training/inference pipeline is minimally documented and needs user setup.

ratings.documentation.rating: 8.0

ratings.documentation.reason: GitHub repo contains core components, but more structured setup instructions and pretrained weights would improve usability.

id: beam_controlCitations: [2], [3]



7 Ultrafast jet classification at the HL-LHC

date: 2024-07-08

last updated: 2024-07

expired: unkown

valid: yes

url: https://arxiv.org/pdf/2402.01876

domain: Particle Physics

focus: FPGA-optimized real-time jet origin classification at the HL-LHC

keywords: - jet classification - FPGA - quantization-aware training - Deep Sets - Interaction Networks

task types: - Classification

ai capability measured: - Real-time inference under FPGA constraints

metrics: - Accuracy - Latency - Resource utilizationmodels: - MLP - Deep Sets - Interaction Network

ml motif: - Real-time

type: Model

ml task: Supervised Learning

notes: Uses quantization-aware training; hardware synthesis evaluated via hls4ml

contact.name: Patrick Odagiu

contact.email: unkown

dataset.name: Zenodo DOI:10.5281/zenodo.3602260

dataset.url: constituent-level jets results.name: ChatGPT LLM

 $\textbf{results.url:} \quad \text{https://docs.google.com/document/d/1gDf1CIYtfmfZ9urv1jCRZMYz} \quad 3 \\ \text{WwEETkugUC65OZBdw} \quad \text{WwEETkugUC65OZBdw} \quad \text{WwEETkugUC65OZBdw} \quad \text{Wweether} \quad \text{Wweether}$

fair.reproducible: True fair.benchmark_ready: False ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 8.0

ratings.specification.reason: Task is clear (RL control of beam stability), with BOOSTR-based simulator; control objectives are well motivated, but system constraints and reward structure are still under refinement.

ratings.dataset.rating: 7.0

ratings.dataset.reason: BOOSTR dataset exists and is cited, but integration into the benchmark is in early stages; metadata and FAIR structure are limited.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Stability and control loss are mentioned, but metrics are not yet formalized with clear definitions or baselines.

ratings.reference solution.rating: 5.5

ratings.reference_solution.reason: DDPG baseline mentioned; PPO planned; implementation is still in progress with no reproducible results available yet.

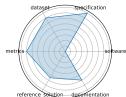
ratings.documentation.rating: 6.0

ratings.documentation.reason: GitHub has a defined structure but is incomplete; setup and execution instructions for training/evaluation are not fully established.

id: ultrafast_jet_classification_at_the_hl-lhc

Citations: [4]

Ultrafast jet classification at the HL-LHC



8 Quench detection

date: 2024-10-15 **last updated:** 2024-10

expired: unkown

valid: yes

url: https://indico.cern.ch/event/1387540/contributions/6153618/attachments/2948441/5182077/fast ml magnets 2024 final.pdf

domain: Accelerators and Magnets

 ${\bf focus:}~$ Real-time detection of superconducting magnet quenches using ML

keywords: - quench detection - autoencoder - anomaly detection - real-time

task types: - Anomaly detection - Quench localization

ai capability measured: - Real-time anomaly detection with multi-modal sensors

metrics: - ROC-AUC - Detection latency

models: - Autoencoder - RL agents (in development)

ml motif: - Real-time, RL

type: Benchmark

ml task: Reinforcement + Unsupervised Learning

notes: Precursor detection in progress; multi-modal and dynamic weighting methods

contact.name: Maira Khan
contact.email: unkown

dataset.name: BPM and power supply data from BNL

dataset.url: HDF5 preprocessed results.name: ChatGPT LLM fair.reproducible: in progress fair.benchmark_ready: False ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 10.0

ratings.specification.reason: Real-time jet origin classification under FPGA constraints is clearly defined, with explicit

latency targets (~100 ns) and I/O formats.

ratings.dataset.rating: 9.0

 $\textbf{ratings.dataset.reason:} \quad \text{Data available on Zenodo with DOI, includes constituent-level jets; accessible and well-documented,} \\$

though not deeply versioned with full FAIR metadata.

ratings.metrics.rating: 10.0

 $\textbf{ratings.metrics.reason:} \quad \text{Accuracy, latency, and hardware resource usage (LUTs, DSPs) are rigorously measured and aligned and aligned the resource of t$

with real-time goals.

 ${\bf ratings.reference_solution.rating:} \quad 9.0$

ratings.reference_solution.reason: Includes models (MLP, Deep Sets, Interaction Networks) with quantization-aware training and synthesis results via hls4ml; reproducible but tightly coupled with specific toolchains.

ratings.documentation.rating: 8.0

ratings.documentation.reason: Paper and code (via hls4ml) are sufficient, but a centralized, standalone repo for reproducing all models would enhance accessibility.

id: quench_detection

9 DUNE

date: 2024-10-15

last updated: 2024-10

expired: unkown

valid: yes

 $\textbf{url:} \quad \text{https://indico.fnal.gov/event/} \\ 66520/\text{contributions/301423/attachments/182439/250508/fast_ml_dunedaq_sonic_10_15_24.pdf$

domain: Particle Physics

focus: Real-time ML for DUNE DAQ time-series data keywords: - DUNE - time-series - real-time - trigger

task_types: - Trigger selection - Time-series anomaly detectionai capability measured: - Low-latency event detection

metrics: - Detection efficiency - Latency
models: - CNN - LSTM (planned)
ml_motif: - Real-time, Time-series
type: Benchmark (in progress)
ml_task: Supervised Learning

notes: Prototype models demonstrated on SONIC platform

contact.name: Andrew J. Morgan

contact.email: unkown

dataset.name: DUNE SONIC data
dataset.url: via internal FNAL systems

results.name: ChatGPT LLM fair.reproducible: in progress fair.benchmark_ready: False ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 8.0

ratings.specification.reason: Task (quench detection via anomaly detection) is clearly described; multi-modal sensors, streaming rates, and objective are provided, but constraints (latency thresholds) are qualitative.

ratings.dataset.rating: 7.0

ratings.dataset.reason: Custom dataset using real data from BNL; HDF5 formatted and structured, but access may be internal or limited, and not versioned for public FAIR use.

ratings.metrics.rating: 8.0

ratings.metrics.reason: ROC-AUC and detection latency are defined; relevant and quantitative but not yet paired with benchmark baselines.

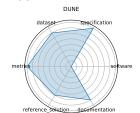
ratings.reference solution.rating: 6.0

ratings.reference_solution.reason: Autoencoder prototype exists; RL methods are in development; no fully reproducible pipeline is available yet.

ratings.documentation.rating: 7.0

ratings.documentation.reason: Slides and GDocs outline results; implementation is in progress with limited setup/code release.

id: duneCitations: [5]



10 Intelligent experiments through real-time AI

date: 2025-01-08

 $last_updated: 2025-01$

expired: unkown

valid: yes

url: https://arxiv.org/pdf/2501.04845

domain: Instrumentation and Detectors; Nuclear Physics; Particle Physics

focus: Real-time FPGA-based triggering and detector control for sPHENIX and future EIC keywords: - FPGA - Graph Neural Network - hls4ml - real-time inference - detector control

 ${f task}$ ${f types:}$ - Trigger classification - Detector control - Real-time inference

ai capability measured: - Low-latency GNN inference on FPGA

metrics: - Accuracy (charm and beauty detection) - Latency (micros) - Resource utilization (LUT/FF/BRAM/DSP)

models: - Bipartite Graph Network with Set Transformers (BGN-ST) - GarNet (edge-classifier)

ml motif: - Real-time

type: Model

ml task: Supervised Learning

notes: Achieved ~97.4% accuracy for beauty decay triggers; sub-10 micros latency on Alveo U280; hit-based FPGA design via hls4ml and FlowGNN.

contact.name: Jakub Kvapil (lanl.gov)

contact.email: unkown

dataset.name: Internal simulated tracking data dataset.url: sPHENIX and EIC DIS-electron tagger

results.name: ChatGPT LLM fair.reproducible: True fair.benchmark_ready: False ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 8.0

ratings.specification.reason: Task (trigger-level anomaly detection) is clearly defined for low-latency streaming input, but the problem framing lacks complete architectural/system specs.

ratings.dataset.rating: 6.0

ratings.dataset.reason: Internal DUNE SONIC data; not publicly released and no formal FAIR support; replicability is institutionally gated.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Metrics include detection efficiency and latency, which are relevant, but only lightly supported by baselines or formal eval scripts.

ratings.reference solution.rating: 5.0

ratings.reference_solution.reason: One CNN prototype demonstrated; LSTM planned. No public implementation or ready-to-run example yet.

ratings.documentation.rating: 6.0

ratings.documentation.reason: Slides and some internal documentation exist, but no full pipeline or public GitHub repovet

id: intelligent experiments through real-time ai

Citations: [6]

Intelligent experiments through real-time Al



11 Neural Architecture Codesign for Fast Physics Applications

date: 2025-01-09 **last_updated:** 2025-01

expired: unkown

valid: yes

url: https://arxiv.org/abs/2501.05515

domain: Physics; Materials Science; Particle Physics

focus: Automated neural architecture search and hardware-efficient model codesign for fast physics applications

keywords: - neural architecture search - FPGA deployment - quantization - pruning - hls4ml

task types: - Classification - Peak finding

ai capability measured: - Hardware-aware model optimization; low-latency inference

metrics: - Accuracy - Latency - Resource utilization

 $\mathbf{models:}\;$ - NAC-based BraggNN - NAC-optimized Deep Sets (jet)

ml motif: - Real-time, Image/CV

type: Framework

ml task: Supervised Learning

notes: Demonstrated two case studies (materials science, HEP); pipeline and code open-sourced.

contact.name: Jason Weitz (UCSD), Nhan Tran (FNAL)

contact.email: unkown

 ${\bf results.name:} \quad {\bf ChatGPT} \ {\bf LLM}$

fair.reproducible: Yes (nac-opt, hls4ml)

fair.benchmark_ready: False
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 10.0

ratings.specification.reason: Task is clearly defined (triggering on rare events with sub-10 micros latency); architecture, constraints, and system context (FPGA, Alveo) are well detailed.

ratings.dataset.rating: 7.0

ratings.dataset.reason: Simulated tracking data from sPHENIX and EIC; internally structured but not yet released in a public FAIR-compliant format.

ratings.metrics.rating: 10.0

ratings.metrics.reason: Accuracy, latency, and hardware resource utilization (LUTs, DSPs) are clearly defined and used in evaluation.

ratings.reference_solution.rating: 9.0

ratings.reference_solution.reason: Graph-based models (BGN-ST, GarNet) are implemented and tested on real hardware; reproducibility possible with hls4ml but full scripts not bundled.

ratings.documentation.rating: 8.0

ratings.documentation.reason: Paper is detailed and tool usage (FlowGNN, hls4ml) is described, but repo release and dataset access remain in progress.

 ${\bf id:} \quad {\rm neural_architecture_codesign_for_fast_physics_applications}$

Citations: [7]

Neural Architecture Codesign for Fast Physics Applications

reference white descentation

12 Smart Pixels for LHC

date: 2024-06-24

last updated: 2024-06

expired: unkown

valid: yes

url: https://arxiv.org/abs/2406.14860

domain: Particle Physics; Instrumentation and Detectors

focus: On-sensor, in-pixel ML filtering for high-rate LHC pixel detectors keywords: - smart pixel - on-sensor inference - data reduction - trigger

task types: - Image Classification - Data filtering

ai capability measured: - On-chip - low-power inference; data reduction

metrics: - Data rejection rate - Power per pixel

models: - 2-layer pixel NN

ml motif: - Real-time, Image/CV

type: Benchmark

ml task: Image Classification

notes: Prototype in CMOS 28 nm; proof-of-concept for Phase III pixel upgrades.

contact.name: Lindsey Gray; Jennet Dickinson

contact.email: unkown
results.name: ChatGPT LLM

fair.reproducible: True

fair.benchmark ready: Yes (Zenodo:7331128)

ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 9.0

ratings.specification.reason: Task (automated neural architecture search for real-time physics) is well formulated with clear latency, model compression, and deployment goals.

ratings.dataset.rating: 6.0

ratings.dataset.reason: Internal Bragg and jet datasets used; not publicly hosted or FAIR-compliant, though mentioned in

the paper.

ratings.metrics.rating: 10.0

ratings.metrics.reason: BOP reduction, latency, and accuracy are all quantitatively evaluated.

 ${\bf ratings.reference_solution.rating:} \quad 8.0$

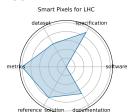
ratings.reference_solution.reason: NAC-generated models for Bragg peak and jet classification are described, but pipeline requires integration of several tools and is not fully packaged.

ratings.documentation.rating: 7.0

ratings.documentation.reason: NAC pipeline, hls4ml usage, and results are discussed; code (e.g., nac-opt) referenced, but replication requires stitching together toolchain and data.

id: smart_pixels_for_lhc

Citations: [8]



13 HEDM (BraggNN)

date: 2023-10-03

 ${\bf last_updated:} \ \ 2023\text{-}10$

expired: unkown

valid: yes

url: https://arxiv.org/abs/2008.08198

domain: Material Science

focus: Fast Bragg peak analysis using deep learning in diffraction microscopy

keywords: - BraggNN - diffraction - peak finding - HEDM

task types: - Peak detection

ai capability measured: - High-throughput peak localization

metrics: - Localization accuracy - Inference time

models: - BraggNN

ml motif: - Real-time, Image/CV

type: Frameworkml task: Peak finding

notes: Enables real-time HEDM workflows; basis for NAC case study.

contact.name: Jason Weitz (UCSD)

contact.email: unkown

results.name: ChatGPT LLM

fair.reproducible: True

fair.benchmark_ready: True
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 10.0

ratings.specification.reason: Fully specified: describes task (data filtering/classification, system design (on-sensor infer-

ence), latency (25 ns), and power constraints.

ratings.dataset.rating: 8.0

ratings.dataset.reason: In-pixel charge cluster data used, but dataset release info is minimal; FAIR metadata/versioning

limited.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Data rejection rate and power per pixel are clearly defined and directly tied to hardware goals.

ratings.reference solution.rating: 9.0

ratings.reference_solution.reason: 2-layer NN implementation is evaluated in hardware; reproducible via hls4ml flow

with results in paper.

 ${\bf ratings. documentation. rating:} \quad 8.0$

ratings.documentation.reason: Paper is clear; Zenodo asset is referenced, but additional GitHub or setup repo would improve reproducibility.

id: hedm_braggnnCitations: [9]

HEDM (BraggNN)
dataset
specification
metrics
softwa

reference solution documentation

14 4D-STEM

date: 2023-12-03

 ${\bf last_updated:} \ \ 2023\text{-}12$

expired: unkown

valid: yes

url: https://openreview.net/pdf?id=7yt3N0o0W9

domain: Material Science

focus: Real-time ML for scanning transmission electron microscopy

keywords: - 4D-STEM - electron microscopy - real-time - image processing

task types: - Image Classification - Streamed data inference

ai capability measured: - Real-time large-scale microscopy inference

metrics: - Classification accuracy - Throughput

models: - CNN models (prototype) ml motif: - Real-time, Image/CV

type: Model

ml task: Image Classification

notes: In-progress; model design under development.

contact.name: unkown
contact.email: unkown
results.name: ChatGPT LLM
fair.reproducible: in progress
fair.benchmark_ready: False
ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9.0

 $\textbf{ratings.specification.reason:} \quad \text{Peak localization task is well-defined for diffraction images; input/output described clearly,} \\$

but no system constraints.
ratings.dataset.rating: 8.0

ratings.dataset.reason: Simulated diffraction images provided; reusable and downloadable, but not externally versioned or

FAIR-structured.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Inference speed and localization accuracy are standard and quantitatively reported.

 ${\bf ratings.reference_solution.rating:} \quad 8.0$

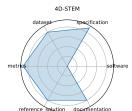
ratings.reference_solution.reason: BraggNN model and training pipeline exist, but need stitching from separate reposi-

tories.

ratings.documentation.rating: 8.0

ratings.documentation.reason: Paper and codebase are available and usable, though not fully turnkey.

id: d-stemCitations: [10]



15 In-Situ High-Speed Computer Vision

date: 2023-12-05 **last_updated:** 2023-12 **expired:** unkown

valid: yes

url: https://arxiv.org/abs/2312.00128

domain: Fusion/Plasma

focus: Real-time image classification for in-situ plasma diagnostics

keywords: - plasma - in-situ vision - real-time ML

task types: - Image Classification

ai capability measured: - Real-time diagnostic inference

metrics: - Accuracy - FPS

models: - CNN

ml motif: - Real-time, Image/CV

type: Model

ml task: Image Classification

notes: Embedded/deployment details in progress.

contact.name: unkown
contact.email: unkown
results.name: ChatGPT LLM

 $\textbf{results.url:} \quad \text{https://docs.google.com/document/d/1EqkRHuQs1yQqMvZs_L6p9JAy2vKX5OCTubzttFBuRoQ/edit?usp=sharing} \\ \text{thtps://docs.google.com/document/d/1EqkRHuQs1yQqMvZs_L6p9JAy2vKX5OCTubzttFBuRoQ/edit?usp=sharing} \\ \text{thtps://document/d/1EqkRHuQs1yQqMvZs_L6p9JAy2vKX5OCTubzttFBuRoQ/edit?usp=sharing} \\ \text{thtps://document/d/1EqkRHuQs1yQqMvZs_L6p9JAy2vMyZs_L6p9JAy2vMyZs_L6p9JAy2vMyZs_L6p9JAy2vMyZs_L6p9JAy2vMyZs_L6p9JAy2vMyZs_L6p9JAy2vMyZs_L6p9JAy2vMyZs_L6p9JAy2vMy$

fair.reproducible: in progress fair.benchmark_ready: False ratings.software.rating: 0

 ${\bf ratings.software.reason:} \quad {\rm Not \ analyzed.}$

ratings.specification.rating: 7.0

ratings.specification.reason: General task defined (real-time microscopy inference), but no standardized I/O format, latency constraint, or complete problem framing yet.

ratings.dataset.rating: 0.0

ratings.dataset.reason: Dataset not provided or described in any formal way.

ratings.metrics.rating: 6.0

ratings.metrics.reason: Mentions throughput and accuracy, but metrics are not formally defined or benchmarked.

ratings.reference solution.rating: 2.0

ratings.reference solution.reason: Prototype CNNs described; no baseline or implementation released.

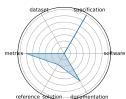
ratings.documentation.rating: 5.0

ratings.documentation.reason: OpenReview paper and Gemini doc give some insight, but no working code, environment, or example.

 $\mathbf{id:} \quad \mathrm{in\text{-}situ_high\text{-}speed_computer_vision}$

Citations: [11]

In-Situ High-Speed Computer Vision



16 BenchCouncil AIBench

date: 2020-01-01

 $last_updated: 2020-01$

expired: unkown

valid: yes

url: https://www.benchcouncil.org/AIBench/

domain: General

focus: End-to-end AI benchmarking across micro, component, and application levels

keywords: - benchmarking - AI systems - application-level evaluation

task types: - Training - Inference - End-to-end AI workloads

ai capability measured: - System-level AI workload performance

metrics: - Throughput - Latency - Accuracy

models: - ResNet - BERT - GANs - Recommendation systems

ml_motif: - General
type: Benchmark
ml task: NA

notes: Covers scenario-distilling, micro, component, and end-to-end benchmarks.

contact.name: Wanling Gao (BenchCouncil)

contact.email: unkown
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

 ${\bf ratings.software.reason:} \quad {\rm Not \ analyzed.}$

ratings.specification.rating: 8.0

ratings.specification.reason: Task (plasma diagnostic classification) and real-time deployment described; system specs (FPS targets) implied but not fully quantified.

ratings.dataset.rating: 6.0

ratings.dataset.reason: Dataset is sensor stream-based but not shared or FAIR-documented.

ratings.metrics.rating: 8.0

ratings.metrics.reason: FPS and classification accuracy reported and relevant.

ratings.reference solution.rating: 7.0

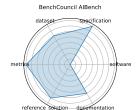
ratings.reference _solution.reason: CNN model described and evaluated, but public implementation and benchmarks are not available yet.

ratings.documentation.rating: 6.0

ratings.documentation.reason: Paper and Gemini doc exist, but full setup instructions and tools are still in progress.

id: benchcouncil aibench

Citations: [12]



17 BenchCouncil BigDataBench

date: 2020-01-01

 $last_updated: 2020-01$

expired: unkown

valid: yes

url: https://www.benchcouncil.org/BigDataBench/

domain: General

focus: Big data and AI benchmarking across structured, semi-structured, and unstructured data workloads

keywords: - big data - AI benchmarking - data analytics

task types: - Data preprocessing - Inference - End-to-end data pipelines

ai capability measured: - Data processing and AI model inference performance at scale

metrics: - Data throughput - Latency - Accuracymodels: - CNN - LSTM - SVM - XGBoost

ml_motif: - General
type: Benchmark
ml task: NA

notes: Built on eight data motifs; provides Hadoop, Spark, Flink, MPI implementations.

contact.name: Jianfeng Zhan (BenchCouncil)

contact.email: unkown
results.name: ChatGPT LLM

 $\textbf{results.url:} \quad \text{https://docs.google.com/document/d/1VFRxhR2G5A83S8PqKBrP99LLVgcCGvX2WW4vTtwxmQ4/edit?usp=sharing} \\ \text{The properties of the properties$

fair.reproducible: Yes fair.benchmark_ready: Yes ratings.software.rating: 0

 ${\bf ratings.software.reason:} \quad {\bf Not \ analyzed.}$

ratings.specification.rating: 9.0

ratings.specification.reason: Evaluates AI at multiple levels (micro to end-to-end); tasks and workloads are clearly defined, though specific I/O formats and constraints vary.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Realistic datasets across diverse domains; FAIR structure for many components, but individual datasets may not all be versioned or richly annotated.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Latency, throughput, and accuracy clearly defined for end-to-end tasks; consistent across models and setups.

ratings.reference solution.rating: 8.0

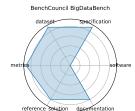
ratings.reference solution.reason: Reference implementations for several tasks exist, but setup across all tasks is complex and not fully streamlined.

ratings.documentation.rating: 8.0

ratings.documentation.reason: Central documentation exists, with detailed component breakdowns; environment setup across platforms (e.g., hardware variations) can require manual adjustment.

 ${\bf id:}\quad bench council_big databench$

Citations: [13]



18 MLPerf HPC

date: 2021-10-20

 ${\bf last_updated:} \ \ 2021\text{--}10$

expired: unkown

valid: yes

url: https://github.com/mlcommons/hpc

domain: Cosmology, Climate, Protein Structure, Catalysis
focus: Scientific ML training and inference on HPC systems
keywords: - HPC - training - inference - scientific ML

task types: - Training - Inference

ai capability measured: - Scaling efficiency - training time - model accuracy on HPC

metrics: - Training time - Accuracy - GPU utilization
 models: - CosmoFlow - DeepCAM - OpenCatalyst
 ml motif: - HPC/inference, HPC/training

type: Framework ml task: NA

notes: Shared framework with MLCommons Science; reference implementations included.

contact.name: Steven Farrell (MLCommons)

contact.email: unkown
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 9.0

ratings.specification.reason: Focused on structured/unstructured data pipelines; clearly defined tasks spanning analytics to AI; some scenarios lack hardware constraint modeling.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Built from 13 real-world sources; structured for realistic big data scenarios; partially FAIR-compliant with documented data motifs.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Covers data throughput, latency, and accuracy; quantitative and benchmark-ready.

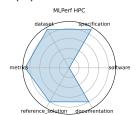
 ${\bf ratings.reference_solution.rating:} \quad 8.0$

ratings.reference solution.reason: Many pipeline and model examples provided using Hadoop/Spark/Flink; setup effort varies by task and platform.

ratings.documentation.rating: 8.0

ratings.documentation.reason: Strong documentation with examples and task specifications; centralized support exists, but task-specific tuning may require domain expertise.

id: mlperf_hpcCitations: [14]



19 MLCommons Science

date: 2023-06-01

last updated: 2023-06

expired: unkown

valid: yes

url: https://github.com/mlcommons/science

domain: Earthquake, Satellite Image, Drug Discovery, Electron Microscope, CFD

focus: AI benchmarks for scientific applications including time-series, imaging, and simulation

keywords: - science AI - benchmark - MLCommons - HPC

task_types: - Time-series analysis - Image classification - Simulation surrogate modeling ai capability measured: - Inference accuracy - simulation speed-up - generalization

 $\mathbf{metrics:}\;$ - MAE - Accuracy - Speedup vs simulation

models: - CNN - GNN - Transformer

ml motif: - Time-series, Image/CV, HPC/inference

type: Framework ml task: NA

notes: Joint national-lab effort under Apache-2.0 license.contact.name: MLCommons Science Working Group

contact.email: unkown
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 10.0

 $\textbf{ratings.specification.reason:} \quad \text{Scientific ML tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level and tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with tasks (e.g., CosmoFlow, CosmoFlow, DeepCAM) are clearly defined with tasks (e.g., CosmoFlow, DeepCAM) are clearly def$

constraints and targets.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Public scientific datasets (e.g., cosmology, weather); used consistently, though FAIR-compliance of individual datasets varies slightly.

ratings.metrics.rating: 10.0

ratings.metrics.reason: Training time, GPU utilization, and accuracy are all directly measured and benchmarked across HPC systems.

ratings.reference_solution.rating: 9.0

ratings.reference_solution.reason: Reference implementations available and actively maintained; HPC setup may require domain-specific environment.

ratings.documentation.rating: 9.0

ratings.documentation.reason: GitHub repo and papers provide detailed instructions; reproducibility supported across multiple institutions.

id: mlcommons science

Citations: [15]



20 LHC New Physics Dataset

date: 2021-07-05

last updated: 2021-07

expired: unkown

valid: yes

url: https://arxiv.org/pdf/2107.02157

domain: Particle Physics; Real-time Triggering

focus: Real-time LHC event filtering for anomaly detection using proton collision data

keywords: - anomaly detection - proton collision - real-time inference - event filtering - unsupervised ML

task types: - Anomaly detection - Event classification

ai capability measured: - Unsupervised signal detection under latency and bandwidth constraints

metrics: - ROC-AUC - Detection efficiency

models: - Autoencoder - Variational autoencoder - Isolation forest

ml_motif: - Multiple
type: Framework
ml task: NA

notes: Includes electron/muon-filtered background and black-box signal benchmarks; 1M events per black box.

contact.name: Ema Puljak (ema.puljak@cern.ch)

contact.email: unkown

dataset.name: Zenodo stores: background + 3 black-box signal sets

dataset.url: 1M events each results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analysed. ratings.specification.rating: 7.0

ratings.specification.reason: The problem (anomaly detection for new physics at LHC) is clearly described with goals and background, but lacks a formal task specification or constraints.

ratings.dataset.rating: 8.0

ratings.dataset.reason: Large-scale, public dataset derived from LHC simulations; well-documented and available via Zen-

odo.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Provides AUROC, accuracy, and anomaly detection metrics but lacks standardized evaluation

script.

ratings.reference solution.rating: 5.0

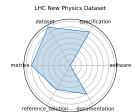
ratings.reference_solution.reason: Baseline models (autoencoders, GANs) are described in associated papers, but implementations vary across papers.

ratings.documentation.rating: 6.0

ratings.documentation.reason: Publicly available papers and datasets with descriptions, but no unified README or training setup.

id: lhc_new_physics_dataset

Citations: [16]



21 MLCommons Medical AI

date: 2023-07-17

last updated: 2023-07

expired: unkown

valid: yes

url: https://github.com/mlcommons/medical

domain: Healthcare; Medical AI

focus: Federated benchmarking and evaluation of medical AI models across diverse real-world clinical data keywords: - medical AI - federated evaluation - privacy-preserving - fairness - healthcare benchmarks

task types: - Federated evaluation - Model validation

ai capability measured: - Clinical accuracy - fairness - generalizability - privacy compliance

metrics: - ROC AUC - Accuracy - Fairness metrics
 models: - MedPerf-validated CNNs - GaNDLF workflows
 ml motif: - Multiple

type: Platform
ml_task: NA

contact.name: Alex Karargyris (MLCommons Medical AI)

contact.email: unkown

dataset.name: Multi-institutional clinical datasets

dataset.url: radiology

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 9.0

ratings.specification.reason: Diverse scientific tasks (earthquake, CFD, microscopy) with detailed problem statements and goals; system constraints not uniformly applied.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Domain-specific datasets (e.g., microscopy, climate); mostly public and structured, but FAIR annotations are not always explicit.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Task-specific metrics (MAE, speedup, accuracy) are clear and reproducible.

ratings.reference solution.rating: 9.0

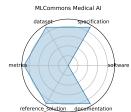
ratings.reference_solution.reason: Reference models (CNN, GNN, Transformer) provided with training/evaluation pipelines.

ratings.documentation.rating: 9.0

ratings.documentation.reason: Well-documented, open-sourced, and maintained with examples; strong community support and reproducibility focus.

id: mlcommons_medical_ai

Citations: [17]



22 CaloChallenge 2022

date: 2024-10-28 last_updated: 2024-10 expired: unkown

valid: yes

url: http://arxiv.org/abs/2410.21611 domain: LHC Calorimeter; Particle Physics

focus: Fast generative-model-based calorimeter shower simulation evaluation

keywords: - calorimeter simulation - generative models - surrogate modeling - LHC - fast simulation

task types: - Surrogate modeling

ai_capability_measured: - Simulation fidelity - speed - efficiencymetrics: - Histogram similarity - Classifier AUC - Generation latency

models: - VAE variants - GAN variants - Normalizing flows - Diffusion models

ml motif: - Surrogate

type: Dataset

ml task: Surrogate Modeling

notes: The most comprehensive survey to date on ML-based calorimeter simulation; 31 submissions over different dataset

sizes.

contact.name: Claudius Krause (CaloChallenge Lead)

contact.email: unkown

dataset.name: Four LHC calorimeter shower datasets

dataset.url: various voxel resolutions
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 9.0

ratings.specification.reason: Task is clearly defined: real-time anomaly detection from high-rate LHC collisions. Latency and bandwidth constraints are mentioned, though not numerically enforced.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Publicly available via Zenodo, with structured signal/background splits, and rich metadata; nearly

fully FAIR.

ratings.metrics.rating: 9.0

ratings.metrics.reason: ROC-AUC and detection efficiency are clearly defined and appropriate for unsupervised anomaly

detection.

ratings.reference solution.rating: 8.0

ratings.reference solution.reason: Several baseline methods (autoencoder, VAE, isolation forest) are evaluated; runnable versions available via community repos but not tightly bundled.

ratings.documentation.rating: 8.0

ratings.documentation.reason: Paper and data documentation are clear, and the dataset is widely reused. Setup requires some manual effort to reproduce full pipelines.

id: calochallenge_Citations: [18]



23 Papers With Code (SOTA Platform)

date: ongoing

last_updated: 2025-06 expired: unkown

valid: yes

url: https://paperswithcode.com/sotadomain: General ML; All domains

focus: Open platform tracking state-of-the-art results, benchmarks, and implementations across ML tasks and papers

keywords: - leaderboard - benchmarking - reproducibility - open-source

task types: - Multiple (Classification, Detection, NLP, etc.)

 ${\bf ai_capability_measured:} \ \ {\rm -Model\ performance\ across\ tasks\ (accuracy\ -\ F1\ -\ BLEU\ -\ etc.)}$

metrics: - Task-specific (Accuracy, F1, BLEU, etc.)

models: - All published models with code

ml_motif: - Multipletype: Platformml task: Multiple

notes: Community-driven open platform; automatic data extraction and versioning.

contact.name: Papers With Code Team

contact.email: unkown
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 9.0

ratings.specification.reason: Evaluation setting (federated clinical benchmarking) is well-defined; I/O interfaces vary slightly by task but are standardized in MedPerf platform.

ratings.dataset.rating: 8.0

ratings.dataset.reason: Uses distributed, real-world clinical datasets across institutions; FAIR compliance varies across

hospitals and data hosts.
ratings.metrics.rating: 9.0

ratings.metrics.reason: ROC AUC, accuracy, and fairness metrics are explicitly defined and task-dependent; consistently tracked across institutions.

ratings.reference solution.rating: 8.0

ratings.reference_solution.reason: Validated CNNs and GaNDLF pipelines are used and shared via the MedPerf tool, but some implementations are abstracted behind the platform.

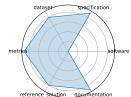
 ${\bf ratings. documentation. rating:} \quad 9.0$

ratings.documentation.reason: Excellent documentation across MedPerf, GaNDLF, and COFE; reproducibility handled via containerized flows and task templates.

 $\mathbf{id:} \quad papers_with_code_sota_platform$

Citations: [19]

Papers With Code (SOTA Platform)



24 Codabench

date: 2022-01-01

last updated: 2025-03

expired: unkown

valid: yes

url: https://www.codabench.org/
domain: General ML; Multiple

focus: Open-source platform for organizing reproducible AI benchmarks and competitions **keywords:** - benchmark platform - code submission - competitions - meta-benchmark

task types: - Multiple

ai capability measured: - Model reproducibility - performance across datasets

metrics: - Submission count - Leaderboard ranking - Task-specific metrics

models: - Arbitrary code submissions

ml_motif: - Multipletype: Platformml task: Multiple

notes: Hosts 51 public competitions, ~26 k users, 177 k submissions :contentReference[oaicite:2]{index=2}

contact.name: Isabelle Guyon (Université Paris-Saclay)

contact.email: unkown
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 10.0

ratings.specification.reason: Simulation task (generative calorimeter showers) is clearly stated with multiple datasets, fidelity requirements, and performance constraints.

ratings.dataset.rating: 9.5

ratings.dataset.reason: Public datasets available in multiple sizes and formats; well-documented; not versioned

ratings.metrics.rating: 10.0

ratings.metrics.reason: Histogram similarity, classifier AUC, and generation latency are clearly defined and benchmarked

 ${\it across \ all \ submissions}.$

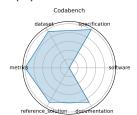
ratings.reference solution.rating: 9.0

ratings.reference_solution.reason: 31 model implementations submitted; some made public and reproducible, though others remain undocumented or private.

ratings.documentation.rating: 9.0

ratings.documentation.reason: Paper, leaderboard, and Gemini doc are comprehensive; unified repo or launchable baseline kit would push this to a 10.

id: codabenchCitations: [20]



25 Sabath (SBI-FAIR)

date: 2021-09-27

 ${\bf last_updated:} \ \ 2023\text{-}07$

expired: unkown

valid: yes

url: https://sbi-fair.github.io/docs/software/sabath/

domain: Systems; Metadata

focus: FAIR metadata framework for ML-driven surrogate workflows in HPC systems

keywords: - meta-benchmark - metadata - HPC - surrogate modeling

task types: - Systems benchmarking

ai capability measured: - Metadata tracking - reproducible HPC workflows

metrics: - Metadata completeness - FAIR compliance

models: - N/A
ml_motif: - Systems
type: Platform
ml_task: NA

notes: Developed by PI Piotr Luszczek at UTK; integrates with MiniWeatherML, AutoPhaseNN, Cosmoflow, etc. :con-

 $tentReference[oaicite:4]{index=4}$

contact.name: Piotr Luszczek (luszczek@utk.edu)

contact.email: unkown

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: N/A
ratings.software.rating: 0

 ${\bf ratings.software.reason:} \quad {\bf Not \ analyzed.}$

ratings.specification.rating: 8.0

ratings.specification.reason: The benchmark defines simulation-based inference (SBI) tasks clearly with FAIR principles

applied to particle physics datasets.

ratings.dataset.rating: 8.0

ratings.dataset.reason: Data is well-structured for SBI and publicly available with clear licensing.

ratings.metrics.rating: 8.0

ratings.metrics.reason: Includes likelihood and posterior accuracy; metrics well-matched to SBI.

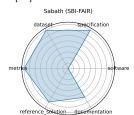
 ${\bf ratings.reference_solution.rating:} \quad 7.0$

 ${\bf ratings.reference_solution.reason:} \quad {\bf Baseline\ SBI\ models\ are\ implemented\ and\ reproducible.}$

ratings.documentation.rating: 6.0

ratings.documentation.reason: GitHub repo includes code and instructions, but lacks full tutorials or walkthroughs.

id: sabath_sbi-fairCitations: [21]



26 PDEBench

date: 2022-10-13

 ${\bf last_updated:} \ \ 2025\text{-}05$

expired: unkown

valid: yes

url: https://github.com/pdebench/PDEBench

domain: CFD; Weather Modeling

focus: Benchmark suite for ML-based surrogates solving time-dependent PDEs keywords: - PDEs - CFD - scientific ML - surrogate modeling - NeurIPS

task types: - Supervised Learning

ai capability measured: - Time-dependent PDE modeling; physical accuracy

metrics: - RMSE - boundary RMSE - Fourier RMSE

models: - FNO - U-Net - PINN - Gradient-Based inverse methods

ml_motif: - Multiple
type: Framework

ml task: Supervised Learning

notes: Datasets hosted on DaRUS (DOI:10.18419/darus-2986); contact maintainers by email :contentRefer-

 $ence[oaicite:6]{index=6}$

contact.name: Makoto Takamoto (makoto.takamoto@neclab.eu)

contact.email: unkown
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

 ${\bf ratings.software.reason:} \quad {\bf Not \ analyzed.}$

ratings.specification.rating: 9.0

ratings.specification.reason: Clearly defined PDE-solving tasks with well-specified constraints and solution formats.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Includes synthetic and real-world PDE datasets with detailed format descriptions.

ratings.metrics.rating: 8.0

ratings.metrics.reason: Uses L2 error and other norms relevant to PDE solutions.

ratings.reference solution.rating: 7.0

ratings.reference solution.reason: Includes baseline solvers and trained models across multiple PDE tasks.

ratings.documentation.rating: 8.0

ratings.documentation.reason: Well-organized GitHub with examples, dataset loading scripts, and training configs.

id: pdebenchCitations: [22]



27 The Well

date: 2024-12-03

 $last_updated: 2025-06$

expired: unkown

valid: yes

url: https://polymathic-ai.org/the well/

domain: biological systems, fluid dynamics, acoustic scattering, astrophysical MHD **focus:** Foundation model + surrogate dataset spanning 16 physical simulation domains

keywords: - surrogate modeling - foundation model - physics simulations - spatiotemporal dynamics

task types: - Supervised Learning

ai capability measured: - Surrogate modeling - physics-based prediction

metrics: - Dataset size - Domain breadth
models: - FNO baselines - U-Net baselines
ml motif: - Foundation model, Surrogate

type: Dataset

ml task: Supervised Learning

notes: Includes unified API and dataset metadata; see 2025 NeurIPS paper for full benchmark details. Size: 15 TB. :contentReference[oaicite:2]{index=2}

contact.name: Wes Brewer contact.email: unkown

dataset.name: 16 simulation datasets dataset.url: HDF5) via PyPI/GitHub results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 7.0

ratings.specification.reason: Explores LLM understanding of mental health scenarios; framing is creative but loosely de-

fined.

 $\textbf{ratings.} \textbf{dataset.} \textbf{rating:} \quad 6.0$

ratings.dataset.reason: Dataset is described in concept but not released; privacy limits public access though synthetic

proxies are referenced.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Uses manual annotation and quality scores, but lacks standardized automatic metrics.

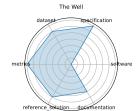
ratings.reference solution.rating: 6.0

ratings.reference solution.reason: Provides few-shot prompt examples and human rating calibration details.

ratings.documentation.rating: 5.0

ratings.documentation.reason: Paper gives use cases, but code and data are not yet public.

id: the_wellCitations: [23]



28 LLM-Inference-Bench

date: 2024-10-31

last updated: 2024-11

expired: unkown

valid: yes

url: https://github.com/argonne-lcf/LLM-Inference-Bench

domain: LLM; HPC/inference

focus: Hardware performance benchmarking of LLMs on AI acceleratorskeywords: - LLM - inference benchmarking - GPU - accelerator - throughput

task types: - Inference Benchmarking

 $\label{limits} \begin{tabular}{ll} \bf ai_capability_measured: & - Inference throughput - latency - hardware utilization \\ \bf metrics: & - Token throughput (tok/s) - Latency - Framework-hardware mix performance \\ \end{tabular}$

models: - LLaMA-2-7B - LLaMA-2-70B - Mistral-7B - Qwen-7B

ml motif: - HPC/inference

type: Dataset

ml task: Inference Benchmarking

notes: Licensed under BSD-3, maintained by Argonne; supports GPUs and accelerators. :contentRefer-

ence[oaicite:4]{index=4}

contact.name: Krishna Teja Chitty-Venkata (Argonne LCF)

contact.email: unkown
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

 ${\bf ratings.software.reason:} \quad {\bf Not \ analyzed.}$

ratings.specification.rating: 9.0

ratings.specification.reason: PDE tasks (forward/inverse) and I/O structures are clearly specified with detailed PDE

context and constraints.

ratings.dataset.rating: 10.0

ratings.dataset.reason: Hosted via DaRUS with a DOI, well-documented, versioned, and FAIR-compliant.

ratings.metrics.rating: 9.0

 ${\bf ratings.metrics.reason:} \quad {\bf Uses} \ {\bf RMSE} \ {\bf variants} \ {\bf and} \ {\bf Fourier-based} \ {\bf errors}.$

ratings.reference_solution.rating: 10.0

ratings.reference_solution.reason: Baselines (FNO, U-Net, PINN) implemented and ready-to-run; strong community

adoption.

ratings.documentation.rating: 9.0

ratings.documentation.reason: Clean GitHub with usage, dataset links, and tutorial notebooks.

id: llm-inference-bench

Citations: [24]

LLM-Inference-Bench
dataset specification
metrics software

reference solution documentation

29 SGLang Framework

date: 2023-12-12

last updated: 2025-06

expired: unkown

valid: yes

url: https://github.com/sgl-project/sglang/tree/main/benchmark

domain: LLM Vision

focus: Fast serving framework for LLMs and vision-language models

keywords: - LLM serving - vision-language - RadixAttention - performance - JSON decoding

task types: - Model serving framework

ai capability measured: - Serving throughput - JSON/task-specific latency metrics: - Tokens/sec - Time-to-first-token - Throughput gain vs baseline

models: - LLaVA - DeepSeek - Llama

ml motif: - LLM Vision

type: Framework

ml task: Model serving

notes: Deployed in production (xAI, NVIDIA, Google Cloud); v0.4.8 release June 2025. :contentReference[oaicite:6]{index=6}

contact.name: SGLang Team

contact.email: unkown

dataset.name: Benchmark configs

dataset.url: dummy or real results.name: ChatGPT LLM

results.url: unkown fair.reproducible: Yes fair.benchmark ready: Yes ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 8.0

ratings.specification.reason: Clearly framed around surrogate learning across 16 domains, but not all tasks are formally posed or constrained in a unified benchmark protocol. Paper mentions performance on NVIDIA H100.

ratings.dataset.rating: 9.0

ratings.dataset.reason: FAIR-compliant physics simulation dataset, structured in HDF5 with unified metadata.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Metrics like dataset size and domain coverage are listed, but standardized quantitative model evaluation metrics (e.g., RMSE, MAE) are not enforced.

ratings.reference solution.rating: 9.0

ratings.reference solution.reason: FNO and U-Net baselines available; full benchmarking implementations pending NeurIPS paper code release.

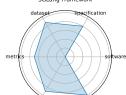
ratings.documentation.rating: 10.0

ratings.documentation.reason: Site and GitHub offer a unified API, metadata standards, and dataset loading tools; NeurIPS paper adds detailed design context.

id: sglang_framework

Citations: [25]

SGLang Framework



30 vLLM Inference and Serving Engine

date: 2023-09-12

 $last_updated: 2025-06$

expired: unkown

valid: yes

url: https://github.com/vllm-project/vllm/tree/main/benchmarks

domain: LLM; HPC/inference

focus: High-throughput, memory-efficient inference and serving engine for LLMs

keywords: - LLM inference - PagedAttention - CUDA graph - streaming API - quantization

task types: - Inference Benchmarking

ai_capability_measured: - Throughput - latency - memory efficiencymetrics: - Tokens/sec - Time to First Token (TTFT) - Memory footprint

models: - LLaMA - Mixtral - FlashAttention-based models

ml motif: - HPC/inference

type: Frameworkml task: Inference

notes: Incubated by LF AI and Data; achieves up to 24x throughput over HuggingFace Transformers :contentRefer-

 $ence[oaicite:2]{index=2}$

contact.name: Woosuk Kwon (vLLM Team)

contact.email: unkown
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 9.0

ratings.specification.reason: Benchmarks hardware performance of LLM inference across multiple platforms with well-defined input/output and platform constraints.

ratings.dataset.rating: 7.0

ratings.dataset.reason: Uses structured log files and configs instead of conventional datasets; suitable for inference bench-

marking.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Clear throughput, latency, and utilization metrics; platform comparison dashboard enhances eval-

uation.

 ${\bf ratings.reference_solution.rating:} \quad 8.0$

ratings.reference_solution.reason: Includes reproducible scripts and example runs; models like LLaMA and Mistral are referenced with platform-specific configs.

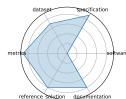
 ${\bf ratings. documentation. rating:} \quad 8.0$

ratings.documentation.reason: GitHub contains clear instructions, platform details, and framework comparisons.

id: vllm_inference_and_serving_engine

Citations: [26]

vLLM Inference and Serving Engine



31 vLLM Performance Dashboard

date: 2022-06-22

 $last_updated: 2025-01$

expired: unkown

valid: yes

url: https://simon-mo-workspace.observablehq.cloud/vllm-dashboard-v0/

domain: LLM; HPC/inference

focus: Interactive dashboard showing inference performance of vLLM

keywords: - Dashboard - Throughput visualization - Latency analysis - Metric tracking

task types: - Performance visualization

ai capability measured: - Throughput - latency - hardware utilization

metrics: - Tokens/sec - TTFT - Memory usage

models: - LLaMA-2 - Mistral - Qwen

ml motif: - HPC/inference

type: Framework
ml task: Visualization

notes: Built using ObservableHQ; integrates live data from vLLM benchmarks.

contact.name: Simon Mo
contact.email: unkown
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 8.0

ratings.specification.reason: Framed as a model-serving tool rather than a benchmark, but includes benchmark configurations and real model tasks.

ratings.dataset.rating: 6.0

ratings.dataset.reason: Mostly uses dummy configs or external model endpoints for evaluation; not designed around a

formal dataset.

ratings.metrics.rating: 8.0

ratings.metrics.reason: Well-defined serving metrics: tokens/sec, time-to-first-token, and gain over baselines.

ratings.reference solution.rating: 9.0

ratings.reference solution.reason: Core framework includes full reproducible serving benchmarks and code; multiple

deployment case studies.

ratings.documentation.rating: 9.0

ratings.documentation.reason: High-quality usage guides, examples, and performance tuning docs.

id: vllm performance dashboard

Citations: [27]

vLLM Performance Dashboard



32 Nixtla NeuralForecast

date: 2022-04-01

last updated: 2025-06

expired: unkown

valid: yes

url: https://github.com/Nixtla/neuralforecastdomain: Time-series forecasting; General ML

focus: High-performance neural forecasting library with >30 models

keywords: - time-series - neural forecasting - NBEATS, NHITS, TFT - probabilistic forecasting - usability

task types: - Time-series forecasting

ai capability measured: - Forecast accuracy - interpretability - speed

 $\mathbf{metrics:}\ \ \text{-}\ \mathrm{RMSE}\ \text{-}\ \mathrm{MAPE}\ \text{-}\ \mathrm{CRPS}$

models: - NBEATS - NHITS - TFT - DeepAR

ml motif: - Time-series

type: Platform

ml task: Forecasting

notes: AutoModel supports hyperparameter tuning and distributed execution via Ray and Optuna. First official NHITS

implementation. content Reference oaicite:4 ndex=4

contact.name: Kin G. Olivares (Nixtla) contact.email: unkown

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9

ratings.specification.reason: Targets high-throughput LLM inference via PagedAttention and memory-optimized serving;

benchmarks cover many configs. ratings.dataset.rating: 7.0

ratings.dataset.reason: Focuses on model configs and streaming input/output pipelines rather than classical datasets.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Strong token/sec, memory usage, and TTFT metrics; comparative plots and logs included.

ratings.reference solution.rating: 9.0

ratings.reference_solution.reason: Benchmarks reproducible via script with support for multiple models and hardware

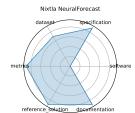
types.

ratings.documentation.rating: 9.0

ratings.documentation.reason: Excellent GitHub docs, CLI/API usage, and deployment walkthroughs.

id: nixtla neuralforecast

Citations: [28]



33 Nixtla Neural Forecast NHITS

date: 2023-06-01

 $last_updated: 2025-06$

expired: unkown

valid: yes

url: https://github.com/Nixtla/neuralforecast

domain: Time-series; General ML

focus: Official NHITS implementation for long-horizon time series forecastingkeywords: - NHITS - long-horizon forecasting - neural interpolation - time-series

task types: - Time-series forecasting

ai capability measured: - Accuracy - compute efficiency for long series

metrics: - RMSE - MAPE

models: - NHITS
ml_motif: - Time-series

type: Platform

ml task: Forecasting

notes: Official implementation in NeuralForecast, included since its AAAI 2023 release.

contact.name: Kin G. Olivares (Nixtla)

contact.email: unkown

dataset.name: Standard forecast datasets

dataset.url: M4

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 7.0

ratings.specification.reason: Primarily a visualization frontend; underlying benchmark definitions come from vLLM

project.

ratings.dataset.rating: 6.0

ratings.dataset.reason: No traditional dataset; displays live or logged benchmark metrics.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Live throughput, memory, latency, and TTFT displayed interactively; highly informative for per-

formance analysis.

ratings.reference solution.rating: 7.0

ratings.reference solution.reason: Dashboard built on vLLM benchmarks but not itself a complete experiment package.

ratings.documentation.rating: 8.0

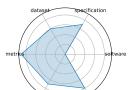
ratings.documentation.reason: Observable notebooks are intuitive; customization instructions are minimal but UI is self-

explanatory.

id: nixtla_neural_forecast_nhits

Citations: [29]

Nixtla Neural Forecast NHITS



reference_solution documentation

34 Nixtla Neural Forecast TimeLLM

date: 2023-10-03

last updated: 2025-06

expired: unkown

valid: yes

url: https://github.com/Nixtla/neuralforecast

domain: Time-series; General ML

focus: Reprogramming LLMs for time series forecasting

keywords: - Time-LLM - language model - time-series - reprogramming

task types: - Time-series forecasting

ai capability measured: - Model reuse via LLM - few-shot forecasting

metrics: - RMSE - MAPEmodels: - Time-LLMml motif: - Time-series

type: Platform

ml task: Forecasting

notes: Fully open-source; transforms forecasting using LLM text reconstruction.

contact.name: Ming Jin (Nixtla)

contact.email: unkown

dataset.name: Standard forecast datasets

dataset.url: M4

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 7.0

ratings.specification.reason: Describes forecasting with LLMs, but less formal on input/output or task framing.

ratings.dataset.rating: 6.0

ratings.dataset.reason: Uses open time series datasets, but lacks a consolidated data release or splits.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Reports metrics like MASE and SMAPE, standard in forecasting.

ratings.reference solution.rating: 6.0

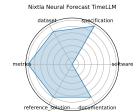
ratings.reference solution.reason: Provides TimeLLM with open source, but no other baselines included.

ratings.documentation.rating: 6.0

ratings.documentation.reason: GitHub readme with installation and example usage; lacks API or extensive tutorials.

id: nixtla_neural_forecast_timellm

Citations: [30]



35 Nixtla Neural Forecast TimeGPT

date: 2023-10-05

 $last_updated: 2025-06$

expired: unkown

valid: yes

url: https://github.com/Nixtla/neuralforecast

domain: Time-series; General ML

focus: Time-series foundation model "TimeGPT" for forecasting and anomaly detection

keywords: - TimeGPT - foundation model - time-series - generative model

task types: - Time-series forecasting - Anomaly detection

ai capability measured: - Zero-shot forecasting - anomaly detection

metrics: - RMSE - Anomaly detection metrics

models: - TimeGPT
ml_motif: - Time-series

type: Platform

ml task: Forecasting

notes: Offered via Nixtla API and Azure Studio; enterprise-grade support available.

contact.name: Azul Garza (Nixtla)

contact.email: unkown

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 7.0

ratings.specification.reason: Describes forecasting with LLMs, but less formal on input/output or task framing.

ratings.dataset.rating: 6.0

ratings.dataset.reason: Uses open time series datasets, but lacks a consolidated data release or splits.

 $\textbf{ratings.metrics.rating:} \quad 7.0$

ratings.metrics.reason: Reports metrics like MASE and SMAPE, standard in forecasting.

ratings.reference solution.rating: 6.0

ratings.reference solution.reason: Provides TimeLLM with open source, but no other baselines included.

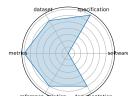
ratings.documentation.rating: 6.0

ratings.documentation.reason: GitHub readme with installation and example usage; lacks API or extensive tutorials.

id: nixtla_neural_forecast_timegpt

Citations: [31]

Nixtla Neural Forecast TimeGPT



36 HDR ML Anomaly Challenge (Gravitational Waves)

date: 2025-03-03

 $last_updated: 2025-03$

expired: unkown

valid: yes

url: https://www.codabench.org/competitions/2626/

domain: Astrophysics; Time-series

focus: Detecting anomalous gravitational-wave signals from LIGO/Virgo datasets **keywords:** - anomaly detection - gravitational waves - astrophysics - time-series

task types: - Anomaly detection

 ${\bf ai_capability_measured:} \ \ {\bf -} \ {\bf Novel} \ {\bf event} \ {\bf detection} \ {\bf in} \ {\bf physical} \ {\bf signals}$

 $\begin{tabular}{ll} \bf metrics: & - ROC\text{-}AUC - Precision/Recall} \\ \bf models: & - Deep \ latent \ CNNs - Autoencoders \\ \end{tabular}$

ml motif: - Time-series

type: Dataset

ml task: Anomaly detection

notes: NSF HDR A3D3 sponsored; prize pool and starter kit provided on Codabench. :contentReference[oaicite:2]{index=2}

contact.name: HDR A3D3 Team

contact.email: unkown

 ${\bf results.name:} \quad {\rm ChatGPT} \ {\rm LLM}$

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 8.0

ratings.specification.reason: Novel approach treating forecasting as text generation is explained; framing is less conven-

tional.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Compatible with standard forecasting datasets (e.g., M4, electricity).

ratings.metrics.rating: 8.0

ratings.metrics.reason: RMSE and MAPE are included, but less emphasis on interpretability or time-series domain con-

straints.

 ${\bf ratings.reference_solution.rating:} \quad 9.0$

ratings.reference_solution.reason: Open-source with reprogramming layers, LLM interface scripts provided.

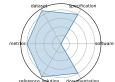
ratings.documentation.rating: 8.0

ratings.documentation.reason: Model and architecture overview present, though usability guide is slightly lighter than others.

id: hdr ml anomaly challenge gravitational waves

Citations: [32]

HDR ML Anomaly Challenge (Gravitational Waves)



37 HDR ML Anomaly Challenge (Butterfly)

date: 2025-03-03

last updated: 2025-03

expired: unkown

valid: yes

url: https://www.codabench.org/competitions/3764/

domain: Genomics; Image/CV

focus: Detecting hybrid butterflies via image anomaly detection in genomic-informed dataset

keywords: - anomaly detection - computer vision - genomics - butterfly hybrids

task types: - Anomaly detection

ai capability measured: - Hybrid detection in biological systems

metrics: - Classification accuracy - F1 score

models: - CNN-based detectors

ml motif: - Image/CV

type: Dataset

ml task: Anomaly detection

notes: Hybrid detection benchmarks hosted on Codabench. :contentReference[oaicite:4]{index=4}

contact.name: Imageomics/HDR Team

contact.email: unkown

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 8.0

 $\textbf{ratings.specification.reason:} \quad \text{Task of detecting rare anomalies in butterfly physics is well-described with physics motivation.}$

ratings.dataset.rating: 7.0

ratings.dataset.reason: Real detector data with injected anomalies is available, but requires NDA for full access.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Uses ROC, F1, and anomaly precision, standard in challenge evaluations.

ratings.reference_solution.rating: 4.0

 ${\bf ratings.reference_solution.reason:} \quad {\bf Partial\ baselines\ described,\ but\ no\ codebase\ or\ reproducible\ runs.}$

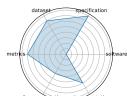
ratings.documentation.rating: 6.0

ratings.documentation.reason: Challenge site includes overview and metrics, but limited in walkthrough or examples.

id: hdr ml anomaly challenge butterfly

Citations: [32]

HDR ML Anomaly Challenge (Butterfly)



38 HDR ML Anomaly Challenge (Sea Level Rise)

date: 2025-03-03 last updated: 2025-03 expired: unkown valid: yes url: https://www.codabench.org/competitions/3223/ ${\bf domain:} \quad {\bf Climate\ Science;\ Time-series,\ Image/CV}$ focus: Detecting anomalous sea-level rise and flooding events via time-series and satellite imagery keywords: - anomaly detection - climate science - sea-level rise - time-series - remote sensing task types: - Anomaly detection ai capability measured: - Detection of environmental anomalies metrics: - ROC-AUC - Precision/Recall models: - CNNs, RNNs, Transformers ml motif: - Time-series, Image/CV type: Dataset ml task: Anomaly detection notes: Sponsored by NSF HDR; integrates sensor and satellite data. :contentReference[oaicite:6]{index=6} contact.name: HDR A3D3 Team contact.email: unkown results.name: ChatGPT LLM results.url: unkown fair.reproducible: Yes fair.benchmark ready: Yes ratings.software.rating: 0 ratings.software.reason: TBD ratings.specification.rating: 9.0 ratings.specification.reason: Clear anomaly detection objective framed for physical signal discovery (LIGO/Virgo). ratings.dataset.rating: 10.0 ratings.dataset.reason: Preprocessed waveform data from dual interferometers, public and well-structured. ratings.metrics.rating: 9.0 ratings.metrics.reason: ROC-AUC, Precision/Recall, and confusion-based metrics are standardized. ratings.reference solution.rating: 1.0 ratings.reference solution.reason: No starter model or baseline code linked ratings.documentation.rating: 9.0 ratings.documentation.reason: Codabench page, GitHub starter kit, and related papers provide strong guidance. id: hdr ml anomaly challenge sea level rise Citations: [32] HDR ML Anomaly Challenge (Sea Level Rise)

39 Single Qubit Readout on QICK System

date: 2025-01-24

 $last_updated: 2025-02$

expired: unkown

valid: yes

url: https://github.com/fastmachinelearning/ml-quantum-readout

domain: Quantum Computing

focus: Real-time single-qubit state classification using FPGA firmware

keywords: - qubit readout - hls4ml - FPGA - QICK

task types: - Classification

ai capability measured: - Single-shot fidelity - inference latency

metrics: - Accuracy - Latencymodels: - hls4ml quantized NNml motif: - Real-time

type: Benchmark

ml task: Supervised Learning

notes: Achieves ~96% fidelity with ~32 ns latency and low FPGA resource utilization. :contentReference[oaicite:1]{index=1}

contact.name: Javier Campos, Giuseppe Di Guglielmo

contact.email: unkown

dataset.name: Zenodo: ml-quantum-readout dataset

dataset.url: zenodo.org/records/14427490

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 8.0

ratings.specification.reason: Task clearly framed around detecting hybrid species via images, but exact labeling methods

and hybrid definitions may need elaboration.

ratings.dataset.rating: 8.0

ratings.dataset.reason: Dataset hosted on Codabench; appears structured but details on image sourcing and labeling

pipeline are limited.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Classification accuracy and F1 are standard and appropriate.

ratings.reference solution.rating: 1.0

ratings.reference solution.reason: No starter model or baseline code linked

ratings.documentation.rating: 7.5

ratings.documentation.reason: Codabench task page describes dataset and evaluation method but lacks full API/docs.

 $\mathbf{id:} \quad \mathbf{single_qubit_readout_on_qick_system}$

Citations: [33]

Single Qubit Readout on QICK System

metries softwar

40 GPQA: A Graduate-Level Google-Proof Question and Answer Benchmark

date: 2023-11-20 last updated: 2023-11expired: unkown valid: yes $\mathbf{url:} \quad https://arxiv.org/abs/2311.12022$ domain: Science (Biology, Physics, Chemistry) focus: Graduate-level, expert-validated multiple-choice questions hard even with web access keywords: - Google-proof - multiple-choice - expert reasoning - science QA task types: - Multiple choice ai capability measured: - Scientific reasoning - knowledge probing metrics: - Accuracy models: - GPT-4 baseline ml motif: - Multiple choice type: Benchmark ml task: Multiple choice notes: Google-proof, supports oversight research. contact.name: David Rein (NYU) contact.email: unkown dataset.name: GPQA dataset dataset.url: zip/HuggingFace results.name: ChatGPT LLM results.url: unkown fair.reproducible: Yes fair.benchmark ready: Yes ratings.software.rating: 0 ratings.software.reason: Not analyzed. ratings.specification.rating: 9.0 ratings.specification.reason: Clear dual-modality task (image + time-series); environmental focus is well described. ratings.dataset.rating: 9.0 ratings.dataset.reason: Time-series and satellite imagery data provided; sensor info and collection intervals are explained. ratings.metrics.rating: 9.0 ratings.metrics.reason: ROC-AUC, Precision/Recall are appropriate and robust. ratings.reference solution.rating: 1.0ratings.reference solution.reason: No starter model or baseline code linked ratings.documentation.rating: 6.5 ratings.documentation.reason: Moderate Codabench documentation with climate context; lacks pipeline-level walkthrough. id: gpqa_a_graduate-level_google-proof_question_and_answer_benchmark Citations: [34]

41 SeafloorAI

date: 2024-12-13

 $last_updated: 2024-12$

expired: unkown

valid: yes

url: https://neurips.cc/virtual/2024/poster/97432

domain: Marine Science; Vision-Language

focus: Large-scale vision-language dataset for seafloor mapping and geological classification

keywords: - sonar imagery - vision-language - seafloor mapping - segmentation - QA

task types: - Image segmentation - Vision-language QA

ai capability measured: - Geospatial understanding - multimodal reasoning

metrics: - Segmentation pixel accuracy - QA accuracymodels: - SegFormer - ViLT-style multimodal models

ml motif: - Vision-Language

type: Dataset

ml task: Segmentation, QA

notes: Data processing code publicly available, covering five geological layers; curated with marine scientists :contentReference[oaicite:2]{index=2}.

contact.name: Kien X. Nguyen

contact.email: unkown

dataset.name: Sonar imagery + annotations

dataset.url: ~15 TB

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9.0

ratings.specification.reason: Real-time qubit classification task clearly defined in quantum instrumentation context.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Dataset available on Zenodo with signal traces; compact and reproducible.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Accuracy and latency are well defined and crucial in this setting.

ratings.reference solution.rating: 9.0

ratings.reference solution.reason: GitHub repo has reproducible code and HLS firmware targeting FPGA.

ratings.documentation.rating: 8.0

ratings.documentation.reason: Good setup instructions, but no interactive visualization or starter notebook.

id: seaflooraiCitations: [35]



42 SuperCon3D

date: 2024-12-13

 $last_updated: 2024-12$

expired: unkown

valid: yes

url: https://neurips.cc/virtual/2024/poster/97553 domain: Materials Science; Superconductivity

focus: Dataset and models for predicting and generating high-Tc superconductors using 3D crystal structures

keywords: - superconductivity - crystal structures - equivariant GNN - generative models

task types: - Regression (Tc prediction) - Generative modeling

ai capability measured: - Structure-to-property prediction - structure generation

metrics: - MAE (Tc) - Validity of generated structures

models: - SODNet - DiffCSP-SC
ml_motif: - Materials Modeling

type: Dataset + Models

ml task: Regression, Generation

notes: Demonstrates advantage of combining ordered and disordered structural data in model design :contentRefer-

ence[oaicite:4]{index=4}.
contact.name: Zhong Zuo

contact.email: unkown
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 10.0

ratings.specification.reason: Multimodal task (segmentation + natural language QA pairs);.

ratings.dataset.rating: 10.0

ratings.dataset.reason: sonar imagery + masks + descriptions, georeferenced and labeled with QA

ratings.metrics.rating: 9.0

ratings.metrics.reason: Pixel accuracy and QA metrics clearly defined; tasks split by modality.

 ${\bf ratings.reference_solution.rating:} \quad 8.0$

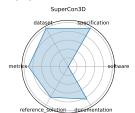
ratings.reference solution.reason: Baseline models (SegFormer, ViLT) are cited, partial configs likely available.

ratings.documentation.rating: 8.5

ratings.documentation.reason: Paper + GitHub metadata and processing details are comprehensive, though full dataset

is not yet available.

id: supercond Citations: [36]



43 GeSS

date: 2024-12-13

last updated: 2024-12

expired: unkown

valid: yes

url: https://neurips.cc/virtual/2024/poster/97816domain: Scientific ML; Geometric Deep Learning

focus: Benchmark suite evaluating geometric deep learning models under real-world distribution shifts keywords: - geometric deep learning - distribution shift - OOD robustness - scientific applications

task types: - Classification - Regression

ai capability measured: - OOD performance in scientific settings

metrics: - Accuracy - RMSE - OOD robustness delta

models: - GCN - EGNN - DimeNet++

ml motif: - Geometric DL

type: Benchmark

ml task: Classification, Regression

notes: Includes no-OOD, unlabeled-OOD, and few-label scenarios :contentReference[oaicite:6]{index=6}.

contact.name: Deyu Zou contact.email: unkown results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

 ${\bf ratings.software.reason:} \quad {\bf Not \ analyzed.}$

ratings.specification.rating: 9.0

ratings.specification.reason: Well-defined problem (Tc prediction, generation) with strong scientific motivation (high-Tc materials), but no formal hardware constraints.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Includes curated 3D crystal structures and Tc data; readily downloadable and used in paper models.

ratings.metrics.rating: 9.0

ratings.metrics.reason: MAE and structural validity used, well-established in materials modeling.

ratings.reference solution.rating: 8.0

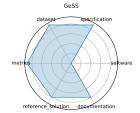
ratings.reference_solution.reason: Provides two reference models (SODNet, DiffCSP-SC) with results. Code likely available post-conference.

ratings.documentation.rating: 8.0

ratings.documentation.reason: Paper and poster explain design choices well; software availability confirms reproducibility but limited external documentation.

id: gess

Citations: [37]



44 Vocal Call Locator (VCL)

date: 2024-12-13

 ${\bf last_updated:} \ \ 2024\text{-}12$

expired: unkown

valid: yes

url: https://neurips.cc/virtual/2024/poster/97470

domain: Neuroscience; Bioacoustics

focus: Benchmarking sound-source localization of rodent vocalizations from multi-channel audio

keywords: - source localization - bioacoustics - time-series - SSL

task types: - Sound source localization

ai capability measured: - Source localization accuracy in bioacoustic settings

metrics: - Localization error (cm) - Recall/Precision

models: - CNN-based SSL models

ml motif: - Real-time

type: Dataset

ml task: Anomaly detection / localization

notes: Dataset spans real, simulated, and mixed audio; supports benchmarking across data types :contentRefer-

ence[oaicite:2] $\{index=2\}.$

contact.name: Ralph Peterson

contact.email: unkown

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

 ${\bf ratings.software.reason:} \quad {\bf Not \ analyzed.}$

ratings.specification.rating: 9.0

ratings.specification.reason: Clear benchmark scenarios across GDL tasks under multiple real-world shift settings; OOD

settings precisely categorized. ratings.dataset.rating: 8.0

ratings.dataset.reason: Scientific graph datasets provided in multiple shift regimes; standardized splits across domains.

Exact format of data not specified.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Includes base metrics (accuracy, RMSE) plus OOD delta robustness for evaluation under shifts.

 ${\bf ratings.reference \quad solution.rating:} \quad 9.0$

ratings.reference_solution.reason: Multiple baselines (11 algorithms x 3 backbones) evaluated; setup supports repro-

ducible comparison.

 ${\bf ratings. documentation. rating:} \quad 2.0$

ratings.documentation.reason: Paper, poster, and source code provide thorough access to methodology and implementation. Setup instructions and accompanying code not present.

id: vocal_call_locator_vcl

Citations: [38]

Vocal Call Locator (VCL)

dataset specification

metres software

reference solution documentation

45 MassSpecGym

date: 2024-12-13

 $last_updated: 2024-12$

expired: unkown

valid: yes

url: https://neurips.cc/virtual/2024/poster/97823 domain: Cheminformatics; Molecular Discovery

focus: Benchmark suite for discovery and identification of molecules via MS/MS

keywords: - mass spectrometry - molecular structure - de novo generation - retrieval - dataset

task types: - De novo generation - Retrieval - Simulation

ai capability measured: - Molecular identification and generation from spectral data

 $\mathbf{metrics:}\;\;$ - Structure accuracy - Retrieval precision - Simulation MSE

 ${f models:}\ \ \ {
m - Graph-based generative models}\ {
m - Retrieval baselines}$

ml_motif: - Benchmark
type: Dataset + Benchmark

ml task: Generation, retrieval, simulation

notes: Dataset~>1M spectra; open-source GitHub repo; widely cited as a go-to benchmark for MS/MS tasks :contentRefer-

 $ence[oaicite:4]{index=4}.$

contact.name: Roman Bushuiev

contact.email: unkown

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9.0

ratings.specification.reason: Focused on sound source localization for rodent vocalizations in lab settings; well-scoped.

ratings.dataset.rating: 9.5

ratings.dataset.reason: 767000 annotated audio segments across diverse conditions. Minor deduction for no train/test/valid

split.

ratings.metrics.rating: 9.5

ratings.metrics.reason: Localization error, precision/recall used

 ${\bf ratings.reference_solution.rating:} \quad 7.0$

ratings.reference_solution.reason: CNN-based baselines referenced but unclear whether pretrained models or training

code are available.

ratings.documentation.rating: 2.0

ratings.documentation.reason: Poster and paper outline benchmark intent and setup; repo expected but not confirmed in

dataset card.

id: massspecgymCitations: [39]



46 Urban Data Layer (UDL)

date: 2024-12-13

 ${\bf last_updated:} \ \ 2024\text{-}12$

expired: unkown

valid: yes

url: https://neurips.cc/virtual/2024/poster/97837domain: Urban Computing; Data Engineering

focus: Unified data pipeline for multi-modal urban science research keywords: - data pipeline - urban science - multi-modal - benchmark

task types: - Prediction - Classification

ai capability measured: - Multi-modal urban inference - standardization

metrics: - Task-specific accuracy or RMSE

models: - Baseline regression/classification pipelines

ml motif: - Data engineering

type: Framework

ml task: Prediction, classification

 $\label{eq:notes:content} \textbf{notes:} \quad \text{Source code available on GitHub (SJTU-CILAB/udl); promotes reusable urban-science foundation models :contentReference[oaicite:6]{index=6}.$

contact.name: Yiheng Wang contact.email: unkown

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed. ratings.specification.rating: 9.0

 $\textbf{ratings.specification.reason:} \quad \text{Three tasks (de novo generation, retrieval, simulation) are clearly defined for MS/MS molecule} \quad \text{Three tasks (de novo generation, retrieval, simulation)} \quad \text{Three tasks (de novo generation)} \quad \text{Thre$

discovery.

ratings.dataset.rating: 10.0

ratings.dataset.reason: Over 1 million spectra with structure annotations; dataset is open-source and well-documented.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Task-appropriate metrics (structure accuracy, precision, MSE) are specified and used consistently.

 ${\bf ratings.reference_solution.rating:} \quad 8.0$

ratings.reference_solution.reason: Baseline models are available (graph-based and retrieval), though not exhaustive.

ratings.documentation.rating: 9.0

ratings.documentation.reason: GitHub repo and poster provide code and reproducibility guidance.

 $\mathbf{id:} \quad \mathbf{urban_data_layer_udl}$

Citations: [40]

dataset specification
metrics software

Urban Data Layer (UDL)

47 Delta Squared-DFT

date: 2024-12-13

 ${\bf last_updated:} \ \ 2024\text{-}12$

expired: unkown

valid: yes

url: https://neurips.cc/virtual/2024/poster/97788 domain: Computational Chemistry; Materials Science

focus: Benchmarking machine-learning corrections to DFT using Delta Squared-trained models for reaction energies

keywords: - density functional theory - Delta Squared-ML correction - reaction energetics - quantum chemistry

task types: - Regression

ai capability measured: - High-accuracy energy prediction - DFT correction

metrics: - Mean Absolute Error (eV) - Energy ranking accuracy

models: - Delta Squared-ML correction networks - Kernel ridge regression

ml_motif: - Scientific ML type: Dataset + Benchmark

ml task: Regression

notes: Demonstrates CC-level accuracy with ~1% of high-level data. Benchmarks publicly included for reproducibility.

contact.name: Wei Liu
contact.email: unkown
results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

 ${\bf ratings.software.reason:} \quad {\rm Not \ analyzed.}$

ratings.specification.rating: 8.0

 $\textbf{ratings.specification.reason:} \quad \text{Clear goals around unifying urban data formats and tasks (e.g., air quality prediction), though} \\$

some specifics could be more formal. ratings.dataset.rating: 9.0

ratings.dataset.reason: Multi-modal data is standardized and accessible; GitHub repo available.

ratings.metrics.rating: 8.0

 $\textbf{ratings.metrics.reason:} \quad \text{Uses common task metrics like accuracy/RMSE, though varies by task.}$

 ${\bf ratings.reference_solution.rating:} \quad 7.0$

 ${\bf ratings.reference_solution.reason:} \quad {\bf Baseline\ regression/classification\ models\ included}.$

ratings.documentation.rating: 8.0

ratings.documentation.reason: Source code supports pipeline reuse, but formal evaluation splits may vary.

 $\mathbf{id:} \quad \mathbf{delta_squared\text{-}dft}$

Citations: [41]



48 LLMs for Crop Science

date: 2024-12-13 **last updated:** 2024-12

expired: unkown

valid: yes

url: https://neurips.cc/virtual/2024/poster/97570

domain: Agricultural Science; NLP

focus: Evaluating LLMs on crop trait QA and textual inference tasks with domain-specific prompts

keywords: - crop science - prompt engineering - domain adaptation - question answering

task types: - Question Answering - Inference

ai capability measured: - Scientific knowledge - crop reasoning

metrics: - Accuracy - F1 score

models: - GPT-4 - LLaMA-2-13B - T5-XXL

ml_motif: - NLP type: Dataset

ml task: QA, inference

notes: Includes examples with retrieval-augmented and chain-of-thought prompt templates; supports few-shot adaptation.

contact.name: Deepak Patel
contact.email: unkown

 ${\bf results.name:} \quad {\rm ChatGPT} \ {\rm LLM}$

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

ratings.software.reason: Not analyzed.

 ${\bf ratings.specification.rating:} \quad 9.0$

ratings.specification.reason: The task of ML correction to DFT energy predictions is well-specified.

ratings.dataset.rating: 9.0

 ${\bf ratings. dataset. reason:} \quad 10 \ {\bf public} \ {\bf reaction} \ {\bf datasets} \ {\bf with} \ {\bf DFT} \ {\bf and} \ {\bf CC} \ {\bf references}; \ {\bf well-documented}.$

ratings.metrics.rating: 8.0

ratings.metrics.reason: Uses MAE and ranking accuracy, suitable for this task.

ratings.reference solution.rating: 8.0

ratings.reference solution.reason: Includes both Delta^2 and KRR baselines.

ratings.documentation.rating: 9.0

ratings.documentation.reason: Public benchmarks and clear reproducibility via datasets and model code.

id: llms_for_crop_science

Citations: [42]

LLMs for Crop Science

Ratings: reference solution documentation

49 SPIQA (LLM)

date: 2024-12-13

last updated: 2024-12

expired: unkown

valid: yes

url: https://neurips.cc/virtual/2024/poster/97575 domain: Multimodal Scientific QA; Computer Vision

focus: Evaluating LLMs on image-based scientific paper figure QA tasks (LLM Adapter performance)

 $\textbf{keywords:} \quad \text{- multimodal QA - scientific figures - image} \\ + \text{text - chain-of-thought prompting}$

task types: - Multimodal QA

ai capability measured: - Visual reasoning - scientific figure understanding

metrics: - Accuracy - F1 score

models: - LLaVA - MiniGPT-4 - Owl-LLM adapter variants

ml motif: - Multimodal QA

type: Benchmark

ml task: Multimodal QA

notes: Companion to SPIQA main benchmark; compares adapter strategies using same images and QA pairs.

contact.name: Xiaoyan Zhong

contact.email: unkown

results.name: ChatGPT LLM

results.url: unkown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0

 ${\bf ratings.software.reason:} \quad {\bf Not \ analyzed.}$

ratings.specification.rating: 6.0

ratings.specification.reason: Task of QA over scientific figures is interesting but not fully formalized in input/output terms.

ratings.dataset.rating: 6.0

ratings.dataset.reason: Uses SPIQA dataset with ~10 adapters; figures and questions are included, but not fully open.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Reports accuracy and F1; fair but no visual reasoning-specific metric.

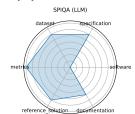
 ${\bf ratings.reference_solution.rating:} \quad 6.0$

 ${\bf ratings.reference_solution.reason:} \quad 10 \ {\rm LLM} \ {\rm adapter} \ {\rm baselines}; \ {\rm results} \ {\rm included}.$

 ${\bf ratings. documentation. rating:} \quad 5.0$

ratings.documentation.reason: Poster paper and limited documentation; no reproducibility instructions.

id: spiqa_llmCitations: [43]



References

- [1] J. Duarte, N. Tran, B. Hawks, et al., Fastml science benchmarks: Accelerating real-time scientific edge machine learning, 2022. arXiv: 2207.07958 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2207.07958.
- J. Duarte, N. Tran, B. Hawks, et al., Fastml science benchmarks: Accelerating real-time scientific edge machine learning, 2022. arXiv: 2207.07958 [cs.LG]. [Online]. Available: https://arxiv.org/abs/ 2207.07958.
- [3] D. Kafkes and J. S. John, *Boostr: A dataset for accelerator control systems*, 2021. arXiv: 2101.08359 [physics.acc-ph]. [Online]. Available: https://arxiv.org/abs/2101.08359.
- [4] P. Odagiu, Z. Que, J. Duarte, et al., Ultrafast jet classification on fpgas for the hl-lhc, 2024. DOI: https://doi.org/10.1088/2632-2153/ad5f10.arXiv: 2402.01876 [hep-ex]. [Online]. Available: https://arxiv.org/abs/2402.01876.
- [5] A. A. Abud, B. Abi, R. Acciarri, et al., Deep underground neutrino experiment (dune) near detector conceptual design report, 2021. arXiv: 2103.13910 [physics.ins-det]. [Online]. Available: https://arxiv.org/abs/2103.13910.
- [6] J. Kvapil, G. Borca-Tasciuc, H. Bossi, et al., Intelligent experiments through real-time ai: Fast data processing and autonomous detector control for sphenix and future eic detectors, 2025. arXiv: 2501. 04845 [physics.ins-det]. [Online]. Available: https://arxiv.org/abs/2501.04845.
- [7] J. Weitz, D. Demler, L. McDermott, N. Tran, and J. Duarte, Neural architecture codesign for fast physics applications, 2025. arXiv: 2501.05515 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2501.05515.
- [8] B. Parpillon, C. Syal, J. Yoo, et al., Smart pixels: In-pixel ai for on-sensor data filtering, 2024. arXiv: 2406.14860 [physics.ins-det]. [Online]. Available: https://arxiv.org/abs/2406.14860.
- [9] Z. Liu, H. Sharma, J.-S. Park, et al., Braggnn: Fast x-ray bragg peak analysis using deep learning, 2021. arXiv: 2008.08198 [eess.IV]. [Online]. Available: https://arxiv.org/abs/2008.08198.
- [10] S. Qin, J. Agar, and N. Tran, "Extremely noisy 4d-tem strain mapping using cycle consistent spatial transforming autoencoders," in *AI for Accelerated Materials Design NeurIPS 2023 Workshop*, 2023. [Online]. Available: https://openreview.net/forum?id=7yt3N0o0W9.
- [11] Y. Wei, R. F. Forelli, C. Hansen, et al., Low latency optical-based mode tracking with machine learning deployed on fpgas on a tokamak, 2024. DOI: https://doi.org/10.1063/5.0190354. arXiv: 2312.00128 [physics.plasm-ph]. [Online]. Available: https://arxiv.org/abs/2312.00128.
- [12] W. Gao, F. Tang, L. Wang, et al., Aibench: An industry standard internet service ai benchmark suite, 2019. arXiv: 1908.08998 [cs.CV]. [Online]. Available: https://arxiv.org/abs/1908.08998.
- [13] W. Gao, J. Zhan, L. Wang, et al., Bigdatabench: A scalable and unified big data and ai benchmark suite, 2018. arXiv: 1802.08254 [cs.DC]. [Online]. Available: https://arxiv.org/abs/1802.08254.
- [14] S. Farrell, M. Emani, J. Balma, et al., Mlperf hpc: A holistic benchmark suite for scientific machine learning on hpc systems, 2021. arXiv: 2110.11466 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2110.11466.
- [15] J. Thiyagalingam, G. von Laszewski, J. Yin, et al., "Ai benchmarking for science: Efforts from the mlcommons science working group," in *High Performance Computing. ISC High Performance 2022 International Workshops*, H. Anzt, A. Bienz, P. Luszczek, and M. Baboulin, Eds., Cham: Springer International Publishing, 2022, pp. 47–64, ISBN: 978-3-031-23220-6.
- [16] T. Aarrestad, E. Govorkova, J. Ngadiuba, E. Puljak, M. Pierini, and K. A. Wozniak, Unsupervised new physics detection at 40 mhz: Training dataset, 2021. DOI: 10.5281/ZENODO.5046389. [Online]. Available: https://zenodo.org/record/5046389.

- [17] A. Karargyris, R. Umeton, M. J. Sheller, et al., "Federated benchmarking of medical artificial intelligence with medperf," Nature Machine Intelligence, vol. 5, no. 7, pp. 799–810, Jul. 2023. DOI: 10.1038/s42256-023-00652-2. [Online]. Available: https://doi.org/10.1038/s42256-023-00652-2.
- [18] C. Krause, M. F. Giannelli, G. Kasieczka, et al., Calochallenge 2022: A community challenge for fast calorimeter simulation, 2024. arXiv: 2410.21611 [physics.ins-det]. [Online]. Available: https://arxiv.org/abs/2410.21611.
- [19] A. Blum and M. Hardt, "The ladder: A reliable leaderboard for machine learning competitions," in *Proceedings of the 32nd International Conference on Machine Learning*, F. Bach and D. Blei, Eds., ser. Proceedings of Machine Learning Research, vol. 37, Lille, France: PMLR, Jul. 2015, pp. 1006–1014. [Online]. Available: https://proceedings.mlr.press/v37/blum15.html.
- [20] Z. Xu, S. Escalera, A. Pavão, et al., "Codabench: Flexible, easy-to-use, and reproducible meta-benchmark platform," Patterns, vol. 3, no. 7, p. 100543, Jul. 2022, ISSN: 2666-3899. DOI: 10.1016/j.patter.2022.100543. [Online]. Available: http://dx.doi.org/10.1016/j.patter.2022.100543.
- [21] P. Luszczek, "Sabath: Fair metadata technology for surrogate benchmarks," University of Tennessee, Tech. Rep., 2021. [Online]. Available: https://github.com/icl-utk-edu/slip/tree/sabath.
- [22] M. Takamoto, T. Praditia, R. Leiteritz, et al., Pdebench: An extensive benchmark for scientific machine learning, 2024. arXiv: 2210.07182 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2210. 07182
- [23] R. Ohana, M. McCabe, L. Meyer, et al., "The well: A large-scale collection of diverse physics simulations for machine learning," in Advances in Neural Information Processing Systems, A. Globerson, L. Mackey, D. Belgrave, et al., Eds., vol. 37, Curran Associates, Inc., 2024, pp. 44989-45037. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/4f9a5acd91ac76569f2fe291b1f4772b-Paper-Datasets_and_Benchmarks_Track.pdf.
- [24] K. T. Chitty-Venkata, S. Raskar, B. Kale, et al., "Llm-inference-bench: Inference benchmarking of large language models on ai accelerators," in SC24-W: Workshops of the International Conference for High Performance Computing, Networking, Storage and Analysis, 2024, pp. 1362–1379. DOI: 10.1109/SCW63240.2024.00178.
- [25] L. Zheng, L. Yin, Z. Xie, et al., Sglang: Efficient execution of structured language model programs, 2024. arXiv: 2312.07104 [cs.AI]. [Online]. Available: https://arxiv.org/abs/2312.07104.
- [26] W. Kwon, Z. Li, S. Zhuang, et al., "Efficient memory management for large language model serving with pagedattention," in *Proceedings of the 29th Symposium on Operating Systems Principles*, ser. SOSP '23, Koblenz, Germany: Association for Computing Machinery, 2023, pp. 611–626. DOI: 10.1145/3600006.3613165. [Online]. Available: https://doi.org/10.1145/3600006.3613165.
- [27] S. Mo, Vllm performance dashboard, 2024. [Online]. Available: https://simon-mo-workspace.observablehq.cloud/vllm-dashboard-v0/.
- [28] K. G. Olivares, C. Challú, F. Garza, M. M. Canseco, and A. Dubrawski, *Neuralforecast: User friendly state-of-the-art neural forecasting models.* PyCon Salt Lake City, Utah, US 2022, 2022. [Online]. Available: https://github.com/Nixtla/neuralforecast.
- [29] C. Challu, K. G. Olivares, B. N. Oreshkin, F. G. Ramirez, M. M. Canseco, and A. Dubrawski, "Nhits: Neural hierarchical interpolation for time series forecasting," in *Proceedings of the AAAI conference on artificial intelligence*, vol. 37, 2023, pp. 6989–6997.
- [30] M. Jin, S. Wang, L. Ma, et al., Time-llm: Time series forecasting by reprogramming large language models, 2024. arXiv: 2310.01728 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2310.01728.
- [31] A. Garza, C. Challu, and M. Mergenthaler-Canseco, *Timegpt-1*, 2024. arXiv: 2310.03589 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2310.03589.

- [32] E. G. Campolongo, Y.-T. Chou, E. Govorkova, et al., Building machine learning challenges for anomaly detection in science, 2025. arXiv: 2503.02112 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2503.02112.
- [33] G. D. Guglielmo, B. Du, J. Campos, et al., End-to-end workflow for machine learning-based qubit readout with qick and hls4ml, 2025. arXiv: 2501.14663 [quant-ph]. [Online]. Available: https://arxiv.org/abs/2501.14663.
- [34] D. Rein, B. L. Hou, A. C. Stickland, et al., Gpqa: A graduate-level google-proof q and a benchmark, 2023. arXiv: 2311.12022 [cs.AI]. [Online]. Available: https://arxiv.org/abs/2311.12022.
- [35] K. X. Nguyen, F. Qiao, A. Trembanis, and X. Peng, Seafloorai: A large-scale vision-language dataset for seafloor geological survey, 2024. arXiv: 2411.00172 [cs.CV]. [Online]. Available: https://arxiv.org/abs/2411.00172.
- [36] P. Chen, L. Peng, R. Jiao, et al., "Learning superconductivity from ordered and disordered material structures," in Advances in Neural Information Processing Systems, A. Globerson, L. Mackey, D. Belgrave, et al., Eds., vol. 37, Curran Associates, Inc., 2024, pp. 108 902-108 928. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/c4e3b55ed4ac9ba52d7df11f8bddbbf4-Paper-Datasets_and_Benchmarks_Track.pdf.
- [37] D. Zou, S. Liu, S. Miao, V. Fung, S. Chang, and P. Li, "Gess: Benchmarking geometric deep learning under scientific applications with distribution shifts," in *Advances in Neural Information Processing Systems*, A. Globerson, L. Mackey, D. Belgrave, et al., Eds., vol. 37, Curran Associates, Inc., 2024, pp. 92499-92528. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/a8063075b00168dc39bc81683619f1a8-Paper-Datasets_and_Benchmarks_Track.pdf.
- [38] R. E. Peterson, A. Tanelus, C. Ick, et al., "Vocal call locator benchmark (vcl) for localizing rodent vocalizations from multi-channel audio," in Advances in Neural Information Processing Systems, A. Globerson, L. Mackey, D. Belgrave, et al., Eds., vol. 37, Curran Associates, Inc., 2024, pp. 106370–106382. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/c00d37d6b04d73b870b963a4d70051c1-Paper-Datasets_and_Benchmarks_Track.pdf.
- [39] R. Bushuiev, A. Bushuiev, N. F. de Jonge, et al., "Massspecgym: A benchmark for the discovery and identification of molecules," in Advances in Neural Information Processing Systems, A. Globerson, L. Mackey, D. Belgrave, et al., Eds., vol. 37, Curran Associates, Inc., 2024, pp. 110 010-110 027. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/c6c31413d5c53b7d1c343c1498734b0f-Paper-Datasets_and_Benchmarks_Track.pdf.
- [40] Y. Wang, T. Wang, Y. Zhang, et al., "Urbandatalayer: A unified data pipeline for urban science," in Advances in Neural Information Processing Systems, A. Globerson, L. Mackey, D. Belgrave, et al., Eds., vol. 37, Curran Associates, Inc., 2024, pp. 7296-7310. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/Odb7f135f6991e8cec5e516ecc66bfba-Paper-Datasets_and_Benchmarks_Track.pdf.
- [41] K. Khrabrov, A. Ber, A. Tsypin, et al., ∇²Dft: A universal quantum chemistry dataset of drug-like molecules and a benchmark for neural network potentials, 2024. arXiv: 2406.14347 [physics.chem-ph]. [Online]. Available: https://arxiv.org/abs/2406.14347.
- [42] T. Shen, H. Wang, J. Zhang, et al., Exploring user retrieval integration towards large language models for cross-domain sequential recommendation, 2024. arXiv: 2406.03085 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2406.03085.
- [43] S. Pramanick, R. Chellappa, and S. Venugopalan, Spiqa: A dataset for multimodal question answering on scientific papers, 2025. arXiv: 2407.09413 [cs.CL]. [Online]. Available: https://arxiv.org/abs/ 2407.09413.