A Living Review of Machine Learning for Particle and Nuclear Physics

Abstract: Modern machine learning techniques, including deep learning, are rapidly being applied, adapted, and developed for high energy particle and nuclear physics. The goal of this document is to provide a nearly comprehensive list of citations for those developing and applying these approaches to experimental, phenomenological, or theoretical analyses. As a living document, it will be updated as often as possible to incorporate the latest developments. A list of proper (unchanging) reviews can be found within. Papers are grouped into a small set of topics to be as useful as possible. Suggestions are most welcome.

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The purpose of this note is to collect references for modern machine learning as applied to particle and nuclear physics. A minimal number of categories is chosen in order to be as useful as possible. Note that papers may be referenced in more than one category. The fact that a paper is listed in this document does not endorse or validate its content - that is for the community (and for peer-review) to decide. Furthermore, the classification here is a best attempt and may have flaws - please let us know if (a) we have missed a paper you think should be included, (b) a paper has been misclassified, or (c) a citation for a paper is not correct or if the journal information is now available. In order to be as useful as possible, this document will continue to evolve so please check back[1] before you write your next paper. You can simply download the .bib file to get all of the latest references. Please consider citing Ref. [1] when referring to this living review.

This review was built with the help of the HEP-ML community, the INSPIRE REST API [2], and the moderators Benjamin Nachman, Matthew Feickert, Claudius Krause, and Ramon Winterhalder.

- **Reviews**
  Below are links to many (static) general and specialized reviews. The third bullet contains links to classic papers that applied shallow learning methods many decades before the deep learning revolution.

  - Modern reviews [3–12]
  - Specialized reviews [13–71]
  - Classical papers [72, 73]
  - Datasets [21, 74–85]

- **Classification**
  Given a feature space $x \in \mathbb{R}^n$, a binary classifier is a function $f : \mathbb{R}^n \to [0,1]$, where 0 corresponds to features that are more characteristic of the zeroth class (e.g. background) and 1 correspond to features that are more characteristic of the one class (e.g. signal). Typically, f will be a function specified by some parameters w (e.g. weights and biases of a neural network) that are determined by minimizing a loss of the form $L[f] = \sum_i \ell(f(x_i), y_i)$, where $y_i \in \{0,1\}$ are labels. The function ℓ is smaller when $f(x_i)$ and y_i are closer. Two common loss functions are the mean squared error $\ell(x,y) = (x-y)^2$ and the binary cross entropy $\ell(x,y) = y\log(x)+(1-y)\log(1-x)$. Exactly what 'more characteristic of'

[1]See https://github.com/iml-wg/HEPML-LivingReview.

means depends on the loss function used to determine f. It is also possible to make a multi-class classifier. A common strategy for the multi-class case is to represent each class as a different basis vector in $\mathbb{R}^{n_{classes}}$ and then $f(x) \in [0,1]^{n_{classes}}$. In this case, $f(x)$ is usually restricted to have its $n_{classes}$ components sum to one and the loss function is typically the cross entropy $\ell(x,y) = \sum_{classes\ i} y_i \log(x)$.

- **Parameterized classifiers** [86–90]
  A classifier that is conditioned on model parameters $f(x|\theta)$ is called a parameterized classifier.
- **Representations**
  There is no unique way to represent high energy physics data. It is often natural to encode x as an image or another one of the structures listed below.
  - **Jet images** [32, 91–111]
    Jets are collimated sprays of particles. They have a complex radiation pattern and such, have been a prototypical example for many machine learning studies. See the next item for a specific description about images.
  - **Event images** [106, 112–126]
    A grayscale image is a regular grid with a scalar value at each grid point. 'Color' images have a fixed-length vector at each grid point. Many detectors are analogous to digital cameras and thus images are a natural representation. In other cases, images can be created by discretizing. Convolutional neural networks are natural tools for processing image data. One downside of the image representation is that high energy physics data tend to be sparse, unlike natural images.
  - **Sequences** [57, 126–130]
    Data that have a variable with a particular order may be represented as a sequence. Recurrent neural networks are natural tools for processing sequence data.
  - **Trees** [131–138]
    Recursive neural networks are natural tools for processing data in a tree structure.
  - **Graphs** [69, 114, 139–236]
    A graph is a collection of nodes and edges. Graph neural networks are natural tools for processing data in a tree structure.
  - **Sets (point clouds)** [80, 97, 237–263]
    A point cloud is a (potentially variable-size) set of points in space. Sets

are distinguished from sequences in that there is no particular order (i.e. permutation invariance). Sets can also be viewed as graphs without edges and so graph methods that can parse variable-length inputs may also be appropriate for set learning, although there are other methods as well.

  * **Physics-inspired basis** [264–282]
    This is a catch-all category for learning using other representations that use some sort of manual or automated physics-preprocessing.

- **Targets**
  * W/Z **tagging** [91, 104, 108, 138, 162, 217, 223, 250, 283–293]
    Boosted, hadronically decaying W and Z bosons form jets that are distinguished from generic quark and gluon jets by their mass near the boson mass and their two-prong substructure.
  * $H \to b\bar{b}$ [106, 113, 123, 139, 162, 220, 229, 293–300]
    Due to the fidelity of b-tagging, boosted, hadronically decaying Higgs bosons (predominantly decaying to $b\bar{b}$) has unique challenged and opportunities compared with W/Z tagging.
  * **quarks and gluons** [95, 98, 103, 107, 137, 217, 231, 250, 294, 301–318]
    Quark jets tend to be narrower and have fewer particles than gluon jets. This classification task has been a benchmark for many new machine learning models.
  * **top quark** tagging [24, 71, 91, 94, 101, 102, 109, 121, 217, 227, 239, 278, 283, 286, 287, 303, 308, 309, 318–341]
    Boosted top quarks form jets that have a three-prong substructure ($t \to Wb, W \to q\bar{q}$).
  * **strange jets** [20, 294, 301, 342–348]
    Strange quarks have a very similar fragmentation to generic quark and gluon jets, so this is a particularly challenging task.
  * b**-tagging** [22, 127, 129, 130, 156, 253, 265, 301, 320, 349–357]
    Due to their long (but not too long) lifetime, the B-hadron lifetime is macroscopic and b-jet tagging has been one of the earliest adapters of modern machine learning tools.
  * **Flavor physics** [151, 156, 264, 358–369]
    This category is for studies related to exclusive particle decays, especially with bottom and charm hadrons.
  * **BSM particles and models** [86, 172, 179, 225, 229, 244, 289, 300, 370–452]

There are many proposals to train classifiers to enhance the presence of particular new physics models.

* **Particle identification** [230, 264, 283, 356, 453–482]
  This is a generic category for direct particle identification and categorization using various detector technologies. Direct means that the particle directly interacts with the detector (in contrast with b-tagging).
* **Neutrino Detectors** [68, 149, 169, 174, 207, 212, 213, 216, 221, 237, 457, 458, 483–533]
  Neutrino detectors are very large in order to have a sizable rate of neutrino detection. The entire neutrino interaction can be characterized to distinguish different neutrino flavors.
* **Direct Dark Matter Detectors** [499, 534–546]
  Dark matter detectors are similar to neutrino detectors, but aim to achieve 'zero' background.
* **Cosmology, Astro Particle, and Cosmic Ray physics** [218, 547–594]
  Machine learning is often used in astrophysics and cosmology in different ways than terrestrial particle physics experiments due to a general divide between Bayesian and Frequentist statistics. However, there are many similar tasks and a growing number of proposals designed for one domain that apply to the other. See also https://github.com/georgestein/ml-in-cosmology.
* **Tracking** [128, 210, 211, 214, 222, 235, 260, 595–625]
  Charged particle tracking is a challenging pattern recognition task. This category is for various classification tasks associated with tracking, such as seed selection.
* **Heavy Ions / Nuclear Physics** [37, 40, 92, 96, 115, 116, 122, 310, 317, 453, 564, 626–722]
  Many tools in high energy nuclear physics are similar to high energy particle physics. The physics target of these studies are to understand collective properties of the strong force.

– **Learning strategies**
  There is no unique way to train a classifier and designing an effective learning strategy is often one of the biggest challenges for achieving optimality.

* **Hyperparameters** [602, 723–728]
  In addition to learnable weights w, classifiers have a number of non-

differentiable parameters like the number of layers in a neural network. These parameters are called hyperparameters.

  * **Weak/Semi supervision** [105, 314, 400, 729–751]
    For supervised learning, the labels y_i are known. In the case that the labels are noisy or only known with some uncertainty, then the learning is called weak supervision. Semi-supervised learning is the related case where labels are known for only a fraction of the training examples.
  * **Unsupervised** [248, 325, 596, 752–766]
    When no labels are provided, the learning is called unsupervised.
  * **Reinforcement Learning** [358, 366, 767–778]
    Instead of learning to distinguish different types of examples, the goal of reinforcement learning is to learn a strategy (policy). The prototypical example of reinforcement learning in learning a strategy to play video games using some kind of score as a feedback during the learning.
  * **Quantum Machine Learning** [58, 140, 147, 393, 484, 485, 517, 779, 779–816]
    Quantum computers are based on unitary operations applied to quantum states. These states live in a vast Hilbert space which may have a usefully large information capacity for machine learning.
  * **Feature ranking** [277, 817, 818]
    It is often useful to take a set of input features and rank them based on their usefulness.
  * **Attention** [113, 128, 249, 321, 370, 499, 819, 820]
    This is an ML tool for helping the network to focus on particularly useful features.
  * **Regularization** [821, 822]
    This is a term referring to any learning strategy that improves the robustness of a classifier to statistical fluctuations in the data and in the model initialization.
  * **Optimal Transport** [301, 762, 765, 823–830]
    Optimal transport is a set of tools for transporting one probability density into another and can be combined with other strategies for classification, regression, etc. The above citation list does not yet include papers using optimal transport distances as part of generative model training.

- **Fast inference / deployment**
  There are many practical issues that can be critical for the actual application of machine learning models.

    * **Software** [15, 120, 126, 319, 450, 491, 590, 613, 831–860]
      Strategies for efficient inference for a given hardware architecture.
    * **Hardware/firmware** [144, 187, 202, 219, 224, 492, 607, 608, 834, 861–912]
      Various accelerators have been studied for fast inference that is very important for latency-limited applications like the trigger at collider experiments.
    * **Deployment** [180, 913–919]
      This category is for the deployment of machine learning interfaces, such as in the cloud.

- **Regression**
  In contrast to classification, the goal of regression is to learn a function $f : \mathbb{R}^n \to \mathbb{R}^m$ *for input features* $x \in \mathbb{R}^n$ *and target features* $y \in \mathbb{R}^m$*. The learning setup is very similar to classification, where the network architectures and loss functions may need to be tweaked. For example, the mean squared error is the most common loss function for regression, but the network output is no longer restricted to be between* 0 *and* 1*.*
  - **Pileup** [125, 233, 737, 778, 920–927]
    A given bunch crossing at the LHC will have many nearly simultaneous proton-proton collisions. Only one of those is usually interesting and the rest introduce a source of noise (pileup) that must be mitigating for precise final state reconstruction.
  - **Calibration** [96, 180, 201, 246, 480, 626, 670, 672, 829, 833, 865, 928–977]
    The goal of calibration is to remove the bias (and reduce variance if possible) from detector (or related) effects.
  - **Recasting** [978–984]
    Even though an experimental analysis may provide a single model-dependent interpretation of the result, the results are likely to have important implications for a variety of other models. Recasting is the task of taking a result and interpreting it in the context of a model that was not used for the original analysis.
  - **Matrix elements** [772, 985–1002]
    Regression methods can be used as surrogate models for functions that are too slow to evaluate. One important class of functions are matrix elements, which form the core component of cross section calculations in quantum field theory.

- **Parameter estimation** [152, 595, 667, 671, 819, 851, 920, 1003–1018]
  The target features could be parameters of a model, which can be learned directly through a regression setup. Other forms of inference are described in later sections (which could also be viewed as regression).
- **Parton Distribution Functions (and related)** [905, 1019–1054]
  Various machine learning models can provide flexible function approximators, which can be useful for modeling functions that cannot be determined easily from first principles such as parton distribution functions.
- **Lattice Gauge Theory** [16, 19, 40, 771, 1019, 1047, 1055–1124, 1124–1147]
  Lattice methods offer a complementary approach to perturbation theory. A key challenge is to create approaches that respect the local gauge symmetry (equivariant networks).
- **Function Approximation** [1041, 1044, 1072, 1148–1158]
  Approximating functions that obey certain (physical) constraints.
- **Symbolic Regression** [1021, 1042, 1159–1170]
  Regression where the result is a (relatively) simple formula.
- **Monitoring** [1167, 1171–1183]
  Regression models can be used to monitor experimental setups and sensors.

- **Equivariant networks** [53, 150, 176, 189, 192, 197, 200, 239, 259, 286, 303, 1112, 1117, 1120, 1126, 1136, 1137, 1146, 1147, 1184–1199]
  It is often the case that implementing equivariance or learning symmetries with a model better describes the physics and improves performance

- **Physics-informed neural networks (PINNs) / Neural Operators** [266, 628, 1087, 1200–1205]
  Physics-informed networks are a type of universal function approximators that can embed the knowledge of any physical laws that govern a given data-set in the learning process, and can be described by partial differential equations (PDEs).

- **Decorrelation methods** [451, 817, 831, 1206–1230]
  It it sometimes the case that a classification or regression model needs to be independent of a set of features (usually a mass-like variable) in order to estimate the background or otherwise reduce the uncertainty. These techniques are related to what the machine learning literature calls model 'fairness'.

- **Generative models / density estimation**
  The goal of generative modeling is to learn (explicitly or implicitly) a probability density $p(x)$ for the features $x \in \mathbb{R}^n$. This task is usually unsupervised (no labels).

- **GANs** [21, 479, 480, 805, 856, 1052, 1198, 1231–1311]
  Generative Adversarial Networks [1312] learn $p(x)$ implicitly through the minimax optimization of two networks: one that maps noise to structure $G(z)$ and one a classifier (called the discriminator) that learns to distinguish examples generated from $G(z)$ and those generated from the target process. When the discriminator is maximally 'confused', then the generator is effectively mimicking $p(x)$.
- **(Variational) Autoencoders** [21, 146, 203, 208, 661, 761, 790, 929, 1019, 1259, 1295, 1307, 1313–1336]
  An autoencoder consists of two functions: one that maps x into a latent space z (encoder) and a second one that maps the latent space back into the original space (decoder). The encoder and decoder are simultaneously trained so that their composition is nearly the identity. When the latent space has a well-defined probability density (as in variational autoencoders), then one can sample from the autoencoder by applying the detector to a randomly chosen element of the latent space.
- **(Continuous) Normalizing flows** [16, 21, 133, 252, 573, 657, 734, 794, 824, 896, 944, 953, 986, 993, 1003, 1064, 1083, 1084, 1095, 1104, 1111, 1115, 1118, 1119, 1131, 1134, 1143, 1147, 1151, 1266, 1268, 1322, 1327, 1337–1397]
  Normalizing flows [1398] learn $p(x)$ explicitly by starting with a simple probability density and then applying a series of bijective transformations with tractable Jacobians.
- **Diffusion Models** [21, 168, 240, 247, 640, 922, 986, 1058, 1060, 1065, 1066, 1069, 1102, 1236, 1341, 1344, 1351, 1354, 1359, 1399–1432]
  These approaches learn the gradient of the density instead of the density directly.
- **Transformer Models** [150, 303, 820, 944, 1103, 1190, 1351, 1400, 1427, 1433–1436]
  These approaches learn the density or perform generative modeling using transformer-based networks.
- **Physics-inspired** [1273, 1437–1442]
  A variety of methods have been proposed to use machine learning tools (e.g. neural networks) combined with physical components.
- **Mixture Models** [476, 1443–1447]
  A mixture model is a superposition of simple probability densities. For example, a Gaussian mixture model is a sum of normal probability densities.

Mixture density networks are mixture models where the coefficients in front of the constituent densities as well as the density parameters (e.g. mean and variances of Gaussians) are parameterized by neural networks.

– **Phase space generation** [780, 994, 1337, 1340, 1346, 1347, 1361, 1376, 1392–1394, 1448–1466]
Monte Carlo event generators integrate over a phase space that needs to be generated efficiently and this can be aided by machine learning methods.

– **Gaussian processes** [983, 1000, 1467, 1468]
These are non-parametric tools for modeling the 'time'-dependence of a random variable. The 'time' need not be actual time — for instance, one can use Gaussian processes to model the energy dependence of some probability density.

– **Evaluation of Generative Models** [21, 28, 1177, 1366, 1386, 1469–1471]
Once a generative model is trained, the quality of its samples needs to be determined. This can be done using non-parametric methods or other machine learning models, for example classifiers.

– **Other/hybrid** [331, 1322, 1427, 1471–1475]
Architectures that combine different network elements or otherwise do not fit into the other categories.

- **Anomaly detection** [23, 82, 84, 85, 133, 146, 206, 540, 582, 636, 736, 742, 743, 748, 749, 753, 763, 764, 783, 787, 792, 796, 798, 803, 810, 830, 831, 881, 884, 898, 1172, 1176, 1208, 1213, 1313, 1318, 1319, 1321, 1327, 1332, 1335, 1362, 1368, 1373, 1380, 1384, 1391, 1412, 1415, 1426, 1476–1570]
The goal of anomaly detection is to identify abnormal events. The abnormal events could be from physics beyond the Standard Model or from faults in a detector. While nearly all searches for new physics are technically anomaly detection, this category is for methods that are mode-independent (broadly defined). Anomalies in high energy physics tend to manifest as over-densities in phase space (often called 'population anomalies') in contrast to off-manifold anomalies where you can flag individual examples as anomalous.

- **Foundation Models, LLMs** [74, 75, 158, 241, 547, 635, 823, 1571–1583]
A foundation model is a machine learning or deep learning model that is trained on broad data such that it can be applied across a wide range of use cases.

- **Kolmogorov-Arnold Networks (KANs)** [639, 1068, 1437, 1584]
Kolmogorov-Arnold Networks (KANs) are alternatives to standard multi-layer

perceptrons in which instead of fixed activation functions on nodes ("neurons") have learnable activation functions on edges ("weights"). This makes them more expressible and interpretable compared to multi-layer perceptrons.

- **Simulation-based ('likelihood-free') Inference**
  Likelihood-based inference is the case where $p(x|\theta)$ is known and θ can be determined by maximizing the probability of the data. In high energy physics, $p(x|\theta)$ is often not known analytically, but it is often possible to sample from the density implicitly using simulations.

  – **Parameter estimation** [88, 89, 152, 176, 483, 574, 637, 647, 1062, 1187, 1266, 1339, 1345, 1388, 1402, 1403, 1585–1628]
  This can also be viewed as a regression problem, but there the goal is typically to do maximum likelihood estimation in contrast to directly minimizing the mean squared error between a function and the target.

  – **Unfolding** [13, 23, 29, 630, 761, 1291, 1304, 1377, 1383, 1396, 1400, 1429, 1591, 1629–1654]
  This is the task of removing detector distortions. In contrast to parameter estimation, the goal is not to infer model parameters, but instead, the undistorted phase space probability density. This is often also called deconvolution.

  – **Domain adaptation** [89, 456, 823, 1277, 1342, 1358, 1360, 1451, 1628, 1655–1663]
  Morphing simulations to look like data is a form of domain adaptation.

  – **BSM** [191, 785, 830, 1012, 1348, 1477, 1559, 1597, 1622–1626, 1664–1688]
  This category is for parameter estimation when the parameter is the signal strength of new physics.

  – **Differentiable Simulation** [365, 928, 1152, 1350, 1405, 1689–1700]
  Coding up a simulation using a differentiable programming language like TensorFlow, PyTorch, or JAX.

- **Uncertainty Quantification**
  Estimating and mitigating uncertainty is essential for the successful deployment of machine learning methods in high energy physics.

  – **Interpretability** [108, 277, 313, 326, 341, 548, 1027, 1160, 1329, 1525, 1655, 1701–1712]
  Machine learning methods that are interpretable maybe more robust and thus less susceptible to various sources of uncertainty.

  - **Estimation** [104, 489, 879, 1204, 1488, 1632, 1713–1721]
    A first step in reducing uncertainties is estimating their size.
  - **Mitigation** [822, 1221, 1230, 1722–1724]
    This category is for proposals to reduce uncertainty.
  - **Uncertainty- and inference-aware learning** [1469, 1570, 1589, 1590, 1667, 1725–1734]
    The usual path for inference is that a machine learning method is trained for a nominal setup. Uncertainties are then propagated in the usual way. This is suboptimal and so there are multiple proposals for incorporating uncertainties into the learning to get as close to making the final statistical test the target of the machine learning as possible.

- **Formal Theory and ML**
  ML can also be utilized in formal theory.
  - Theory and physics for ML [627, 1406, 1434, 1593, 1735–1746]
  - ML for theory [752, 769, 1201, 1202, 1205, 1314, 1338, 1349, 1420, 1433, 1740, 1747–1756, 1756–1803]

- **Experimental results**
  This section is incomplete as there are many results that directly and indirectly (e.g. via flavor tagging) use modern machine learning techniques. We will try to highlight experimental results that use deep learning in a critical way for the final analysis sensitivity.
  - Performance studies [852, 1804–1812]
  - Searches and measurements where ML reconstruction is a core component [112, 134, 135, 161, 163, 356, 409, 411, 412, 979, 1479, 1487, 1635, 1813–1850]
  - Final analysis discriminate for searches [140, 743, 1184, 1206, 1844, 1851–1855].
  - Measurements using deep learning directly (not through object reconstruction) [1644, 1856]

References

[1] M. Feickert and B. Nachman, *A Living Review of Machine Learning for Particle Physics*, 2102.02770. 1

[2] M. Moskovic, *The INSPIRE REST API*, . 1

[3] P. Shanahan et al., *Snowmass 2021 Computational Frontier CompF03 Topical Group Report: Machine Learning*, 2209.07559. 1

[4] A. Boehnlein et al., *Artificial Intelligence and Machine Learning in Nuclear Physics*, *Rev.Mod.Phys.* **94** (12, 2021) 031003, [2112.02309].

[5] G. Karagiorgi, G. Kasieczka, S. Kravitz, B. Nachman and D. Shih, *Machine Learning in the Search for New Fundamental Physics*, 2112.03769.

[6] M. D. Schwartz, *Modern Machine Learning and Particle Physics*, 2103.12226.

[7] D. Bourilkov, *Machine and Deep Learning Applications in Particle Physics*, *Int. J. Mod. Phys. A* **34** (2020) 1930019, [1912.08245].

[8] G. Carleo, I. Cirac, K. Cranmer, L. Daudet, M. Schuld, N. Tishby et al., *Machine learning and the physical sciences*, *Rev. Mod. Phys.* **91** (2019) 045002, [1903.10563].

[9] A. Radovic, M. Williams, D. Rousseau, M. Kagan, D. Bonacorsi, A. Himmel et al., *Machine learning at the energy and intensity frontiers of particle physics*, *Nature* **560** (2018) 41–48.

[10] K. Albertsson et al., *Machine Learning in High Energy Physics Community White Paper*, 1807.02876.

[11] D. Guest, K. Cranmer and D. Whiteson, *Deep Learning and its Application to LHC Physics*, 1806.11484.

[12] A. J. Larkoski, I. Moult and B. Nachman, *Jet Substructure at the Large Hadron Collider: A Review of Recent Advances in Theory and Machine Learning*, *Phys. Rept.* **841** (2020) 1–63, [1709.04464]. 1

[13] F. Canelli et al., *A Practical Guide to Unbinned Unfolding*, 2507.09582. 1, 10

[14] M. King, *Deep Learning and Model Independence*, 2507.03438.

[15] L. Boggia et al., *Review of Machine Learning for Real-Time Analysis at the Large Hadron Collider experiments ALICE, ATLAS, CMS and LHCb*, 2506.14578. 6

[16] M. C. N. Cheng and N. Stratikopoulou, *Lecture Notes on Normalizing Flows for Lattice Quantum Field Theories*, 2504.18126. 7, 8

[17] C. David, *What is AI, what is it not, how we use it in physics and how it impacts... you*, in *Particle Physics and Cosmology in the Himalayas*, 4, 2025. 2504.01827.

[18] S. Caron et al., *Strategic White Paper on AI Infrastructure for Particle, Nuclear, and Astroparticle Physics: Insights from JENA and EuCAIF*, 2503.14192.

[19] S. Lawrence, *Machine-learning approaches to accelerating lattice simulations*, *PoS* **LATTICE2024** (2025) 010, [2502.02670]. 7

[20] CMS Collaboration, *Run 3 performance and advances in heavy-flavor jet tagging in CMS*, *PoS* **ICHEP2024** (2025) 992, [2412.05863]. 3

[21] C. Krause et al., *CaloChallenge 2022: A Community Challenge for Fast Calorimeter Simulation*, 2410.21611. 1, 8, 9

[22] A. Malara, *Exploring jets: substructure and flavour tagging in CMS and ATLAS*, in *12th Large Hadron Collider Physics Conference*, vol. LHCP2024, p. 150, 10, 2024. 2410.14330. DOI. 3

[23] J. M. Duarte, *Novel machine learning applications at the LHC*, in *42nd International Conference on High Energy Physics*, vol. ICHEP2024, p. 012, 9, 2024. 2409.20413. DOI. 9, 10

[24] R. Sahu, S. Ashanujjaman and K. Ghosh, *Unveiling the Secrets of New Physics Through Top Quark Tagging*, *Eur.Phys.J.ST* **233** (9, 2024) 2465, [2409.12085]. 3

[25] J. Halverson, *TASI Lectures on Physics for Machine Learning*, 2408.00082.

[26] A. J. Larkoski, *QCD Masterclass Lectures on Jet Physics and Machine Learning*, *Eur.Phys.J.C* **84** (7, 2024) 1117, [2407.04897].

[27] R. K. Barman and S. Biswas, *Top-philic Machine Learning*, 2407.00183.

[28] F. Y. Ahmad, V. Venkataswamy and G. Fox, *A Comprehensive Evaluation of Generative Models in Calorimeter Shower Simulation*, 2406.12898. 9

[29] N. Huetsch et al., *The Landscape of Unfolding with Machine Learning*, *SciPost Phys.* **18** (4, 2024) 070, [2404.18807]. 10

[30] S. Mondal and L. Mastrolorenzo, *Machine Learning in High Energy Physics: A review of heavy-flavor jet tagging at the LHC*, 2404.01071.

[31] J. Bardhan, T. Mandal, S. Mitra, C. Neeraj and M. Patra, *Unsupervised and lightly supervised learning in particle physics*, 2403.13676.

[32] H. Kheddar, Y. Himeur, A. Amira and R. Soualah, *High-energy physics image classification: A Survey of Jet Applications*, 2403.11934. 2

[33] J. A. Gooding, L. Bozianu, C. C. Toapaxi, P. Jawahar and M. Olocco, *The SMARTHEP European Training Network*, *EPJ Web Conf.* **295** (2024) 08022, [2401.13484].

[34] J. Y. Araz et al., *Les Houches guide to reusable ML models in LHC analyses*, *SciPost Phys.Comm.Rep.* (12, 2023) 3, [2312.14575].

[35] V. Belis, P. Odagiu and T. K. Årrestad, *Machine Learning for Anomaly Detection in Particle Physics*, *Rev.Phys.* **12** (12, 2023) 100091, [2312.14190].

[36] H. Hashemi and C. Krause, *Deep Generative Models for Detector Signature Simulation: An Analytical Taxonomy*, *Rev.Phys.* **12** (12, 2023) 100092, [2312.09597].

[37] C. Allaire et al., *Artificial Intelligence for the Electron Ion Collider (AI4EIC)*, in *Artificial Intelligence for the Electron Ion Collider*, vol. 8, p. 5, 7, 2023. 2307.08593. DOI. 4

[38] Y.-L. Du, *Overview: Jet quenching with machine learning*, in *11th International Conference on Hard and Electromagnetic Probes of High-Energy Nuclear Collisions: Hard Probes 2023*, 8, 2023. 2308.10035.

[39] G. DeZoort, P. W. Battaglia, C. Biscarat and J.-R. Vlimant, *Graph neural networks at the Large Hadron Collider*, *Nature Rev. Phys.* **5** (4, 2023) 281–303.

[40] K. Zhou, L. Wang, L.-G. Pang and S. Shi, *Exploring QCD matter in extreme conditions with Machine Learning*, *Prog.Part.Nucl.Phys.* **104084** (3, 2023) 2023, [2303.15136]. 4, 7

[41] P. Huber et al., *Snowmass Neutrino Frontier Report*, in *Snowmass 2021*, 11, 2022. 2211.08641.

[42] E. A. Huerta et al., *FAIR for AI: An interdisciplinary, international, inclusive, and diverse community building perspective*, 2210.08973.

[43] T. Cheng, *Bridging Machine Learning and Sciences: Opportunities and Challenges*, 2210.13441.

[44] T. Plehn, A. Butter, B. Dillon and C. Krause, *Modern Machine Learning for LHC Physicists*, 2211.01421.

[45] T. Y. Chen, B. Dey, A. Ghosh, M. Kagan, B. Nord and N. Ramachandra, *Interpretable Uncertainty Quantification in AI for HEP*, in *2022 Snowmass Summer Study*, 8, 2022. 2208.03284. DOI.

[46] G. Benelli et al., *Data Science and Machine Learning in Education*, in *2022 Snowmass Summer Study*, 7, 2022. 2207.09060.

[47] Y. Coadou, *Boosted decision trees*, *Artificial Intelligence for High Energy Physics* (6, 2022) 9, [2206.09645].

[48] P. Harris et al., *Physics Community Needs, Tools, and Resources for Machine Learning*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.16255.

[49] S. Thais, P. Calafiura, G. Chachamis, G. DeZoort, J. Duarte, S. Ganguly et al.,

Graph Neural Networks in Particle Physics: Implementations, Innovations, and Challenges, in *2022 Snowmass Summer Study*, 3, 2022. 2203.12852.

[50] A. Adelmann et al., *New directions for surrogate models and differentiable programming for High Energy Physics detector simulation*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.08806.

[51] C. Dvorkin et al., *Machine Learning and Cosmology*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.08056.

[52] S. Badger et al., *Machine Learning and LHC Event Generation*, *SciPost Phys.* **14** (3, 2022) 079, [2203.07460].

[53] A. Bogatskiy et al., *Symmetry Group Equivariant Architectures for Physics*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.06153. 7

[54] B. Viren, J. Huang, Y. Huang, M. Lin, Y. Ren, K. Terao et al., *Solving Simulation Systematics in and with AI/ML*, in *2022 Snowmass Summer Study*, 3, 2022. 2203.06112.

[55] P. Baldi, P. Sadowski and D. Whiteson, *Deep Learning From Four Vectors*, 2203.03067.

[56] Y. Alanazi, N. Sato, P. Ambrozewicz, A. N. H. Blin, W. Melnitchouk, M. Battaglieri et al., *A survey of machine learning-based physics event generation*, 2106.00643.

[57] R. T. de Lima, *Sequence-based Machine Learning Models in Jet Physics*, 2102.06128. 2

[58] W. Guan, G. Perdue, A. Pesah, M. Schuld, K. Terashi, S. Vallecorsa et al., *Quantum Machine Learning in High Energy Physics*, 2005.08582. 5

[59] M. Kagan, *Image-Based Jet Analysis*, 2012.09719.

[60] D. Rousseau and A. Ustyuzhanin, *Machine Learning scientific competitions and datasets*, 2012.08520.

[61] K. Cranmer, J. Brehmer and G. Louppe, *The frontier of simulation-based inference*, 1911.01429.

[62] J.-R. Vlimant and J. Yin, *Distributed Training and Optimization Of Neural Networks*, 2012.01839.

[63] J. Duarte and J.-R. Vlimant, *Graph Neural Networks for Particle Tracking and Reconstruction*, 2012.01249.

[64] B. Nachman, *Anomaly Detection for Physics Analysis and Less than Supervised Learning*, 2010.14554.

[65] J. Brehmer and K. Cranmer, *Simulation-based inference methods for particle physics*, 2010.06439.

[66] S. Forte and S. Carrazza, *Parton distribution functions*, 2008.12305.

[67] A. Butter and T. Plehn, *Generative Networks for LHC events*, 2008.08558.

[68] F. Psihas, M. Groh, C. Tunnell and K. Warburton, *A Review on Machine Learning for Neutrino Experiments*, 2008.01242. 4

[69] J. Shlomi, P. Battaglia and J.-R. Vlimant, *Graph Neural Networks in Particle Physics*, 2007.13681. 2

[70] T. Dorigo and P. de Castro, *Dealing with Nuisance Parameters using Machine Learning in High Energy Physics: a Review*, 2007.09121.

[71] A. Butter et al., *The Machine Learning Landscape of Top Taggers*, *SciPost Phys.* **7** (2019) 014, [1902.09914]. 1, 3

[72] L. Lonnblad, C. Peterson and T. Rognvaldsson, *Finding Gluon Jets With a Neural Trigger*, *Phys. Rev. Lett.* **65** (1990) 1321–1324. 1

[73] B. H. Denby, *Neural Networks and Cellular Automata in Experimental High-energy Physics*, *Comput. Phys. Commun.* **49** (1988) 429–448. 1

[74] K. G. Barman, S. Caron, F. Hasibi, E. Shalugin, Y. Marcet, J. Otte et al., *Towards a Large Physics Benchmark*, 2507.21695. 1, 9

[75] O. Amram, L. Anzalone, J. Birk, D. A. Faroughy, A. Hallin, G. Kasieczka et al., *Aspen Open Jets: Unlocking LHC Data for Foundation Models in Particle Physics*, *Mach.Learn.Sci.Tech.* **6** (12, 2024) 030601, [2412.10504]. 9

[76] W. Bhimji et al., *FAIR Universe HiggsML Uncertainty Challenge Competition*, 2410.02867.

[77] K. Zoch, J. A. Raine, D. Sengupta and T. Golling, *RODEM Jet Datasets*, 2408.11616.

[78] R. Rusack, B. Joshi, A. Alpana, S. Sharma and T. Vadnais, *Electron Energy Regression in the CMS High-Granularity Calorimeter Prototype*, 2309.06582.

[79] IceCube collaboration, P. Eller, *Public Kaggle Competition "IceCube – Neutrinos in Deep Ice"*, in *38th International Cosmic Ray Conference*, 7, 2023. 2307.15289.

[80] H. Qu, C. Li and S. Qian, *Particle Transformer for Jet Tagging*, 2202.03772. 2

[81] Y. Chen et al., *A FAIR and AI-ready Higgs Boson Decay Dataset*, 2108.02214.

[82] E. Govorkova, E. Puljak, T. Aarrestad, M. Pierini, K. A. Woźniak and J. Ngadiuba, *LHC physics dataset for unsupervised New Physics detection at 40 MHz*, *Sci. Data* **9** (7, 2021) 118, [2107.02157]. 9

[83] L. Benato et al., *Shared Data and Algorithms for Deep Learning in Fundamental Physics*, *Comput.Softw.Big Sci.* **6** (7, 2021) 9, [2107.00656].

[84] T. Aarrestad et al., *The Dark Machines Anomaly Score Challenge: Benchmark Data and Model Independent Event Classification for the Large Hadron Collider*, *SciPost Phys.* **12** (5, 2021) 043, [2105.14027]. 9

[85] G. Kasieczka et al., *The LHC Olympics 2020: A Community Challenge for Anomaly Detection in High Energy Physics*, *Rept.Prog.Phys.* **84** (1, 2021) 124201, [2101.08320]. 1, 9

[86] J. A. Aguilar-Saavedra and S. Rodríguez-Benítez, *Mass-unspecific classifiers for mass-dependent searches*, 2503.20926. 2, 3

[87] S. Chen, A. Glioti, G. Panico and A. Wulzer, *Boosting likelihood learning with event reweighting*, *JHEP* **03** (8, 2023) 117, [2308.05704].

[88] B. Nachman and J. Thaler, *E Pluribus Unum Ex Machina: Learning from Many Collider Events at Once*, *Phys.Rev.D* **103** (1, 2021) 116013, [2101.07263]. 10

[89] K. Cranmer, J. Pavez and G. Louppe, *Approximating Likelihood Ratios with Calibrated Discriminative Classifiers*, 1506.02169. 10

[90] P. Baldi, K. Cranmer, T. Faucett, P. Sadowski and D. Whiteson, *Parameterized neural networks for high-energy physics*, *Eur. Phys. J.* **C76** (2016) 235, [1601.07913]. 2

[91] J. Bassa, V. Manian, S. Malik and A. Chattopadhyay, *Jet Image Tagging Using Deep Learning: An Ensemble Model*, 2508.10034. 2, 3

[92] U. S. Qureshi and R. Kunnawalkam Elayavalli, *Deep Image Reconstruction for Background Subtraction in Heavy-Ion Collisions*, 2507.14036. 4

[93] T. Han, I. M. Lewis, H. Liu, Z. Liu and X. Wang, *A Guide to Diagnosing Colored Resonances at Hadron Colliders*, *JHEP* **08** (5, 2023) 173, [2306.00079].

[94] S. Choi, J. Li, C. Zhang and R. Zhang, *Automatic detection of boosted Higgs and top quark jets in event image*, *Phys.Rev.D* **108** (2, 2023) 116002, [2302.13460]. 3

[95] J. Filipek, S.-C. Hsu, J. Kruper, K. Mohan and B. Nachman, *Identifying the Quantum Properties of Hadronic Resonances using Machine Learning*, *SciPost Phys.Core* **8** (5, 2021) 039, [2105.04582]. 3

[96] Y.-L. Du, D. Pablos and K. Tywoniuk, *Deep learning jet modifications in heavy-ion collisions*, *JHEP* **03** (12, 2020) 206, [2012.07797]. 4, 6

[97] J. Collado, K. Bauer, E. Witkowski, T. Faucett, D. Whiteson and P. Baldi, *Learning to Isolate Muons*, 2021. 10.1007/JHEP10(2021)200. 2

[98] J. S. H. Lee, I. Park, I. J. Watson and S. Yang, *Quark-Gluon Jet Discrimination Using Convolutional Neural Networks*, *J. Korean Phys. Soc.* **74** (2019) 219–223, [2012.02531]. 3

[99] J. Li and H. Sun, *An Attention Based Neural Network for Jet Tagging*, 2009.00170.

[100] J. Li, T. Li and F.-Z. Xu, *Reconstructing boosted Higgs jets from event image segmentation*, *JHEP* **04** (2020) 156, [2008.13529].

[101] S. Macaluso and D. Shih, *Pulling Out All the Tops with Computer Vision and Deep Learning*, *JHEP* **10** (2018) 121, [1803.00107]. 3

[102] G. Kasieczka, T. Plehn, M. Russell and T. Schell, *Deep-learning Top Taggers or The End of QCD?*, *JHEP* **05** (2017) 006, [1701.08784]. 3

[103] P. T. Komiske, E. M. Metodiev and M. D. Schwartz, *Deep learning in color: towards automated quark/gluon jet discrimination*, *JHEP* **01** (2017) 110, [1612.01551]. 3

[104] J. Barnard, E. N. Dawe, M. J. Dolan and N. Rajcic, *Parton Shower Uncertainties in Jet Substructure Analyses with Deep Neural Networks*, *Phys. Rev.* **D95** (2017) 014018, [1609.00607]. 3, 11

[105] P. T. Komiske, E. M. Metodiev, B. Nachman and M. D. Schwartz, *Learning to classify from impure samples with high-dimensional data*, *Phys. Rev. D* **98** (2018) 011502, [1801.10158]. 5

[106] J. Lin, M. Freytsis, I. Moult and B. Nachman, *Boosting $H \to b\bar{b}$ with Machine Learning*, *JHEP* **10** (2018) 101, [1807.10768]. 2, 3

[107] ATLAS Collaboration, *Quark versus Gluon Jet Tagging Using Jet Images with the ATLAS Detector*, Tech. Rep. ATL-PHYS-PUB-2017-017, CERN, Geneva, Jul, 2017. 3

[108] L. de Oliveira, M. Kagan, L. Mackey, B. Nachman and A. Schwartzman, *Jet-images — deep learning edition*, *JHEP* **07** (2016) 069, [1511.05190]. 3, 10

[109] L. G. Almeida, M. Backović, M. Cliche, S. J. Lee and M. Perelstein, *Playing Tag with ANN: Boosted Top Identification with Pattern Recognition*, *JHEP* **07** (2015) 086, [1501.05968]. 3

[110] J. Cogan, M. Kagan, E. Strauss and A. Schwarztman, *Jet-Images: Computer Vision Inspired Techniques for Jet Tagging*, *JHEP* **02** (2015) 118, [1407.5675].

[111] J. Pumplin, *How to tell quark jets from gluon jets*, *Phys. Rev. D* **44** (1991) 2025–2032. 2

[112] IceCube Collaboration, *Fast Low Energy Reconstruction using Convolutional Neural Networks*, 2505.16777. 2, 11

[113] Y. Wu, L. Xiao and Y. Zhang, *Deep Learning to Improve the Sensitivity of Higgs Pair Searches in the 4b Channel at the LHC*, 2505.04496. 3, 5

[114] M. Andriamirado et al., *Machine Learning for Single-Ended Event Reconstruction in PROSPECT Experiment*, *JINST* **20** (3, 2025) P08006, [2503.06727]. 2

[115] P. Murali, S. Dash and B. K. Nandi, *Simultaneous Estimation of Elliptic Flow Coefficient and Impact Parameter in Heavy-Ion Collisions using CNN*, 2411.11001. 4

[116] Y. He et al., *A novel machine learning method to detect double-Λ hypernuclear events in nuclear emulsions*, *Nucl.Instrum.Meth.A* **1073** (9, 2024) 170196, [2409.01657]. 4

[117] K. Ban, K. Kong, M. Park and S. C. Park, *Exploring the Synergy of Kinematics and Dynamics for Collider Physics*, *Phys.Rev.D* **110** (11, 2023) 115035, [2311.16674].

[118] Z.-X. Yang, X.-H. Fan, Z.-P. Li and S. Nishimura, *A Neural Network Approach for Orienting Heavy-Ion Collision Events*, *Phys.Lett.B* **848** (8, 2023) 138359, [2308.15796].

[119] D. Bae et al., *Large-Scale Deep Learning for Multi-Jet Event Classification*, 2207.11710.

[120] A. A. Pol et al., *Jet Single Shot Detection*, *EPJ Web Conf.* **251** (5, 2021) 04027, [2105.05785]. 6

[121] M. Andrews et al., *End-to-End Jet Classification of Boosted Top Quarks with the CMS Open Data*, *EPJ Web Conf.* **251** (4, 2021) 04030, [2104.14659]. 3

[122] Y.-L. Du, K. Zhou, J. Steinheimer, L.-G. Pang, A. Motornenko, H.-S. Zong et al., *Identifying the nature of the QCD transition in relativistic collision of heavy nuclei with deep learning*, *Eur. Phys. J. C* **80** (2020) 516, [1910.11530]. 4

[123] Y.-L. Chung, S.-C. Hsu and B. Nachman, *Disentangling Boosted Higgs Boson Production Modes with Machine Learning*, *JINST* **16** (9, 2020) P07002, [2009.05930]. 3

[124] M. Andrews, M. Paulini, S. Gleyzer and B. Poczos, *End-to-End Physics Event Classification with the CMS Open Data: Applying Image-based Deep Learning on Detector Data to Directly Classify Collision Events at the LHC*, 1807.11916.

[125] ATLAS Collaboration, *Convolutional Neural Networks with Event Images for Pileup Mitigation with the ATLAS Detector*, Tech. Rep. ATL-PHYS-PUB-2019-028, CERN, Geneva, Jul, 2019. 6

[126] T. Q. Nguyen, D. Weitekamp, D. Anderson, R. Castello, O. Cerri, M. Pierini et al., *Topology classification with deep learning to improve real-time event selection at the LHC*, *Comput. Softw. Big Sci.* **3** (2019) 12, [1807.00083]. 2, 6

[127] ATLAS Collaboration, *Identification of Jets Containing b-Hadrons with Recurrent Neural Networks at the ATLAS Experiment*, Tech. Rep. ATL-PHYS-PUB-2017-003, CERN, Geneva, Mar, 2017. 3

[128] K. Goto, T. Suehara, T. Yoshioka, M. Kurata, H. Nagahara, Y. Nakashima et al.,

Development of a Vertex Finding Algorithm using Recurrent Neural Network, 2021. 10.1016/j.nima.2022.167836. 4, 5

[129] E. Bols, J. Kieseler, M. Verzetti, M. Stoye and A. Stakia, *Jet Flavour Classification Using DeepJet*, 2008.10519. 3

[130] D. Guest, J. Collado, P. Baldi, S.-C. Hsu, G. Urban and D. Whiteson, *Jet Flavor Classification in High-Energy Physics with Deep Neural Networks*, *Phys. Rev.* **D94** (2016) 112002, [1607.08633]. 2, 3

[131] A. Choudhury, A. Mondal and S. Sarkar, *Searches for the BSM scenarios at the LHC using decision tree based machine learning algorithms: A comparative study and review of Random Forest, Adaboost, XGboost and LightGBM frameworks*, *Eur.Phys.J.ST* **233** (5, 2024) 2425, [2405.06040]. 2

[132] G. Matousek and A. Vossen, *Photon Classification with Gradient Boosted Trees at CLAS12*, *JINST* **19** (2, 2024) C06006, [2402.13105].

[133] T. Finke, M. Hein, G. Kasieczka, M. Krämer, A. Mück, P. Prangchaikul et al., *Back To The Roots: Tree-Based Algorithms for Weakly Supervised Anomaly Detection*, *Phys.Rev.D* **109** (9, 2023) 034033, [2309.13111]. 8, 9

[134] M. Belfkir, A. Jueid and S. Nasri, *Boosting dark matter searches at muon colliders with Machine Learning: the mono-Higgs channel as a case study*, *PTEP* **2023** (9, 2023) 123B03, [2309.11241]. 11

[135] B. Dutta, T. Ghosh, A. Horne, J. Kumar, S. Palmer, P. Sandick et al., *Applying Machine Learning Techniques to Searches for Lepton-Partner Pair-Production with Intermediate Mass Gaps at the Large Hadron Collider*, *Phys.Rev.D* **109** (9, 2023) 075018, [2309.10197]. 11

[136] M. Jercic, I. Jercic and N. Poljak, *Introduction and analysis of a method for the investigation of QCD-like tree data*, *Entropy* **24** (12, 2021) , [2112.01809].

[137] T. Cheng, *Recursive Neural Networks in Quark/Gluon Tagging*, 1711.02633. 3

[138] G. Louppe, K. Cho, C. Becot and K. Cranmer, *QCD-Aware Recursive Neural Networks for Jet Physics*, 1702.00748. 2, 3

[139] M. Belfkir, M. A. Loualidi and S. Nasri, *Boosting Sensitivity to $HH \to b\bar{b}$ with Graph Neural Networks and XGBoost*, 2508.01449. 2, 3

[140] S. H. Ali, A. Ahmad, M. Saiel and N. Shaukat, *Search for $t\bar{t}t\bar{t}W$ Production at $\sqrt{s} = 13$ TeV Using a Modified Graph Neural Network at the LHC*, 2507.23723. 5, 11

[141] X. Jia, X. Qin, T. Li, X. Zhang, X. Hu, S. Song et al., *Noise Filtering Algorithm Based on Graph Neural Network for STCF Drift Chamber*, 2507.09224.

[142] A. Ferrière and A. Benoit-Lévy, *Reconstruction of cosmic-ray properties with GNN in GRAND*, in *39th International Cosmic Ray Conference*, 7, 2025. 2507.07541.

[143] G. Hijano et al., *Replacing detector simulation with heterogeneous GNNs in flavour physics analyses*, 2507.05069.

[144] M. Neu, I. Haide, T. Justinger, T. Rädler, V. Dajaku, T. Ferber et al., *Real-Time Graph-based Point Cloud Networks on FPGAs via Stall-Free Deep Pipelining*, 2507.05099. 6

[145] K. Menkce, M. McEneaney and A. Vossen, *Direct Vertex Reconstruction of* Λ *Baryons from Hits in CLAS12 using Graph Neural Networks*, 2507.01868.

[146] J. Y. Araz, D. Athanasakos, M. Ploskon and F. Ringer, *Graph theory inspired anomaly detection at the LHC*, 2506.19920. 8, 9

[147] M. Casals, V. Belis, E. F. Combarro, E. Alarcón, S. Vallecorsa and M. Grossi, *Guided Graph Compression for Quantum Graph Neural Networks*, 2506.09862. 5

[148] J. Chan, B. Wang and P. Calafiura, *Physics and Computing Performance of the EggNet Tracking Pipeline*, 2506.03415.

[149] C. Mo and L. Li, *Hybrid-Graph Neural Network Method for Muon Fast Reconstruction in Neutrino Telescopes*, 2505.23425. 4

[150] J. Spinner, L. Favaro, P. Lippmann, S. Pitz, G. Gerhartz, T. Plehn et al., *Lorentz Local Canonicalization: How to Make Any Network Lorentz-Equivariant*, 2505.20280. 7, 8

[151] W. Sutcliffe, M. Calvi, S. Capelli, J. Eschle, J. García Pardiñas, A. Mathad et al., *Scalable Multi-Task Learning for Particle Collision Event Reconstruction with Heterogeneous Graph Neural Networks*, 2504.21844. 3

[152] A. Hammad and A. Jueid, *Progress in* $\mathcal{CP}$ *violating top-Higgs coupling at the LHC with Machine Learning*, 2504.11791. 7, 10

[153] J. Aguilar et al., *Classification of Electron and Muon Neutrino Events for the ESS*ν*SB Near Water Cherenkov Detector using Graph Neural Networks*, 2503.15247.

[154] A. Akram, X. Ju, M. Papenbrock, J. Taylor, T. Stockmanns and K. Schönning, *Application of Geometric Deep Learning for Tracking of Hyperons in a Straw Tube Detector*, 2503.14305.

[155] M. Abumusabh, J. Cerasoli, G. Dujany and C. Santos, *Graph-based Full Event Interpretation: a graph neural network for event reconstruction in Belle II*, 2503.09401.

[156] Belle-II Collaboration, *Graph Neural Network Flavor Tagger and measurement of*

sin2β *at Belle II*, in *58th Rencontres de Moriond on Electroweak Interactions and Unified Theories*, 1, 2025. 2501.17631. 3

[157] D. Ntounis, L. Gouskos and C. Vernieri, *Evaluating the Impact of Detector Design on Jet Flavor Tagging for Future Colliders*, 2501.16584.

[158] J. Ho, B. R. Roberts, S. Han and H. Wang, *Pretrained Event Classification Model for High Energy Physics Analysis*, 2412.10665. 9

[159] L. Reuter et al., *End-to-End Multi-Track Reconstruction using Graph Neural Networks at Belle II*, *Comput.Softw.Big Sci.* **9** (11, 2024) 6, [2411.13596].

[160] N. Kakati, E. Dreyer, A. Ivina, F. A. Di Bello, L. Heinrich, M. Kado et al., *HGPflow: Extending Hypergraph Particle Flow to Collider Event Reconstruction*, *Eur.Phys.J.C* **85** (10, 2024) 847, [2410.23236].

[161] BESIII Collaboration, *Observation of a rare beta decay of the charmed baryon with a Graph Neural Network*, *Nature Commun.* **16** (10, 2024) 681, [2410.13515]. 11

[162] X. Ma, Z. Wu, J. Wu, Y. Huang, G. Li, M. Ruan et al., *Measurements of decay branching fractions of the Higgs boson to hadronic final states at the CEPC*, *Chin.Phys.C* **49** (10, 2024) 053001, [2410.04465]. 3

[163] CMS Collaboration, *Search for light long-lived particles decaying to displaced jets in proton-proton collisions at $\sqrt{s}$ = 13.6 TeV*, *Rept.Prog.Phys.* **88** (9, 2024) 037801, [2409.10806]. 11

[164] P. Calafiura, J. Chan, L. Delabrouille and B. Wang, *EggNet: An Evolving Graph-based Graph Attention Network for Particle Track Reconstruction*, 2407.13925.

[165] A. Correia, F. I. Giasemis, N. Garroum, V. V. Gligorov and B. Granado, *Graph Neural Network-Based Track Finding in the LHCb Vertex Detector*, *JINST* **19** (7, 2024) P12022, [2407.12119].

[166] N. Soybelman, C. Schiavi, F. A. Di Bello and E. Gross, *Accelerating Graph-based Tracking Tasks with Symbolic Regression*, *Mach.Learn.Sci.Tech.* **5** (6, 2024) 045042, [2406.16752].

[167] M. Aamir et al., *Using graph neural networks to reconstruct charged pion showers in the CMS High Granularity Calorimeter*, *JINST* **19** (6, 2024) P11025, [2406.11937].

[168] D. Kobylianskii, N. Soybelman, N. Kakati, E. Dreyer and E. Gross, *Advancing Set-Conditional Set Generation: Graph Diffusion for Fast Simulation of Reconstructed Particles*, *Phys.Rev.D* **110** (5, 2024) 092013, [2405.10106]. 8

[169] A. Aurisano, V. Hewes, G. Cerati, J. Kowalkowski, C. S. Lee, W. Liao et al., *NuGraph2: A Graph Neural Network for Neutrino Physics Event Reconstruction*, *Phys.Rev.D* **110** (3, 2024) 032008, [2403.11872]. 4

[170] E. Pfeffer, M. Waßmer, Y.-Y. Cung, R. Wolf and U. Husemann, *A case study of sending graph neural networks back to the test bench for applications in high-energy particle physics*, *Comput.Softw.Big Sci.* **8** (2, 2024) 13, [2402.17386].

[171] Belle-II Collaboration, *A new graph-neural-network flavor tagger for Belle II and measurement of* $\sin 2\phi_1$ *in* $B^0 \to J/\psi K^0_S$ *decays*, *Phys.Rev.D* **110** (2, 2024) 012001, [2402.17260].

[172] C. Birch-Sykes, B. Le, Y. Peters, E. Simpson and Z. Zhang, *Reconstruction of Short-Lived Particles using Graph-Hypergraph Representation Learning*, *Phys.Rev.D* **111** (2, 2024) 032004, [2402.10149]. 3

[173] Z. Lu, X. Chen, J. Wu, Y. Zhang and L. Li, *Application of Graph Neural Networks in Dark Photon Search with Visible Decays at Future Beam Dump Experiment*, 2401.15477.

[174] C. Mo, F. Zhang and L. Li, *Neutrino Reconstruction in TRIDENT Based on Graph Neural Network*, 2401.15324. 4

[175] L. Heinrich, B. Huth, A. Salzburger and T. Wettig, *Combined track finding with GNN & CKF*, 1, 2024. 2401.16016.

[176] S. Chatterjee, S. S. Cruz, R. Schöfbeck and D. Schwarz, *Rotation-equivariant graph neural network for learning hadronic SMEFT effects*, *Phys. Rev. D* **109** (2024) 076012, [2401.10323]. 7, 10

[177] P. Konar, V. S. Ngairangbam and M. Spannowsky, *Hypergraphs in LHC Phenomenology – The Next Frontier of IRC-Safe Feature Extraction*, *JHEP* **01** (9, 2023) 113, [2309.17351].

[178] D. Murnane, *Graph Structure from Point Clouds: Geometric Attention is All You Need*, 2307.16662.

[179] B. Bhattacherjee, P. Konar, V. S. Ngairangbam and P. Solanki, *LLPNet: Graph Autoencoder for Triggering Light Long-Lived Particles at HL-LHC*, 2308.13611. 3

[180] D. Holmberg, D. Golubovic and H. Kirschenmann, *Jet energy calibration with deep learning as a Kubeflow pipeline*, *Comput. Softw. Big Sci.* **7** (8, 2023) 9, [2308.12724]. 6

[181] Belle II Collaboration, *Photon Reconstruction in the Belle II Calorimeter Using Graph Neural Networks*, *Comput.Softw.Big Sci.* **7** (6, 2023) 13, [2306.04179].

[182] ATLAS Collaboration, *Flavour tagging with graph neural networks with the ATLAS detector*, in *30th International Workshop on Deep-Inelastic Scattering and Related Subjects*, 6, 2023. 2306.04415.

[183] J. García Pardinas, M. Calvi, J. Eschle, A. Mauri, S. Meloni, M. Mozzanica et al., *GNN for Deep Full Event Interpretation and hierarchical reconstruction of*

heavy-hadron decays in proton-proton collisions, *Comput.Softw.Big Sci.* **7** (4, 2023) 12, [2304.08610].

[184] R. Liu, P. Calafiura, S. Farrell, X. Ju, D. T. Murnane and T. M. Pham, *Hierarchical Graph Neural Networks for Particle Track Reconstruction*, in *21th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI meets Reality*, 3, 2023. 2303.01640.

[185] M. McEneaney and A. Vossen, *Domain-adversarial graph neural networks for Λ hyperon identification with CLAS12*, *JINST* **18** (2023) P06002, [2302.05481].

[186] B. Wang, Y. Wang, D. Han, Z. Xiao and Y. Zhang, *Determination of impact parameter for CEE with Digi-input neural networks*, *JINST* **19** (7, 2023) P05009, [2307.15355].

[187] M. Neu, J. Becker, P. Dorwarth, T. Ferber, L. Reuter, S. Stefkova et al., *Real-time Graph Building on FPGAs for Machine Learning Trigger Applications in Particle Physics*, *Comput.Softw.Big Sci.* **8** (7, 2023) 8, [2307.07289]. 6

[188] B. Yu, N. Hartmann, L. Schinnerl and T. Kuhr, *Improved selective background Monte Carlo simulation at Belle II with graph attention networks and weighted events*, in *21th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI meets Reality*, 7, 2023. 2307.06434.

[189] D. Murnane, S. Thais and A. Thete, *Equivariant Graph Neural Networks for Charged Particle Tracking*, in *21th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI meets Reality*, 4, 2023. 2304.05293. 7

[190] L. Ehrke, J. A. Raine, K. Zoch, M. Guth and T. Golling, *Topological Reconstruction of Particle Physics Processes using Graph Neural Networks*, *Phys.Rev.D* **107** (3, 2023) 116019, [2303.13937].

[191] Anisha, O. Atkinson, A. Bhardwaj, C. Englert, W. Naskar and P. Stylianou, *On the BSM reach of four top production at the LHC*, *Phys.Rev.D* **108** (2, 2023) 035001, [2302.08281]. 10

[192] R. T. Forestano, K. T. Matchev, K. Matcheva, A. Roman, E. Unlu and S. Verner, *Deep Learning Symmetries and Their Lie Groups, Algebras, and Subalgebras from First Principles*, *Mach.Learn.Sci.Tech.* **4** (1, 2023) 025027, [2301.05638]. 7

[193] A. Huang, X. Ju, J. Lyons, D. Murnane, M. Pettee and L. Reed, *Heterogeneous Graph Neural Network for identifying hadronically decayed tau leptons at the High Luminosity LHC*, *JINST* **18** (2023) P07001, [2301.00501].

[194] F. Mokhtar, R. Kansal and J. Duarte, *Do graph neural networks learn traditional jet substructure?*, in *36th Conference on Neural Information Processing Systems*, 11, 2022. 2211.09912.

[195] F. A. Di Bello et al., *Reconstructing particles in jets using set transformer and hypergraph prediction networks*, *Eur.Phys.J.C* **83** (12, 2022) 596, [2212.01328].

[196] L. Builtjes, S. Caron, P. Moskvitina, C. Nellist, R. R. de Austri, R. Verheyen et al., *Attention to the strengths of physical interactions: Transformer and graph-based event classification for particle physics experiments*, *SciPost Phys.* **19** (11, 2022) 028, [2211.05143].

[197] A. Bogatskiy, T. Hoffman, D. W. Miller and J. T. Offermann, *PELICAN: Permutation Equivariant and Lorentz Invariant or Covariant Aggregator Network for Particle Physics*, 2211.00454. 7

[198] F. Ma, F. Liu and W. Li, *A jet tagging algorithm of graph network with HaarPooling message passing*, *Phys.Rev.D* **108** (10, 2022) 072007, [2210.13869].

[199] S. R. Qasim, N. Chernyavskaya, J. Kieseler, K. Long, O. Viazlo, M. Pierini et al., *End-to-end multi-particle reconstruction in high occupancy imaging calorimeters with graph neural networks*, *Eur.Phys.J.C* **82** (4, 2022) 753, [2204.01681].

[200] S. Gong, Q. Meng, J. Zhang, H. Qu, C. Li, S. Qian et al., *An Efficient Lorentz Equivariant Graph Neural Network for Jet Tagging*, *JHEP* **07** (1, 2022) 030, [2201.08187]. 7

[201] J. Pata, J. Duarte, F. Mokhtar, E. Wulff, J. Yoo, J.-R. Vlimant et al., *Machine Learning for Particle Flow Reconstruction at CMS*, in *20th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI Decoded - Towards Sustainable, Diverse, Performant and Effective Scientific Computing*, vol. 2438, p. 012100, 3, 2022. 2203.00330. DOI. 6

[202] A. Elabd et al., *Graph Neural Networks for Charged Particle Tracking on FPGAs*, *Front.Big Data* **5** (12, 2021) 828666, [2112.02048]. 6

[203] S. Tsan, R. Kansal, A. Aportela, D. Diaz, J. Duarte, S. Krishna et al., *Particle Graph Autoencoders and Differentiable, Learned Energy Mover's Distance*, in *35th Conference on Neural Information Processing Systems*, 11, 2021. 2111.12849. 8

[204] O. Atkinson, A. Bhardwaj, S. Brown, C. Englert, D. J. Miller and P. Stylianou, *Improved Constraints on Effective Top Quark Interactions using Edge Convolution Networks*, *JHEP* **04** (11, 2021) 137, [2111.01838].

[205] P. Konar, V. S. Ngairangbam and M. Spannowsky, *Energy-weighted Message Passing: an infra-red and collinear safe graph neural network algorithm*, *JHEP* **02** (9, 2021) 060, [2109.14636].

[206] O. Atkinson, A. Bhardwaj, C. Englert, V. S. Ngairangbam and M. Spannowsky, *Anomaly detection with Convolutional Graph Neural Networks*, *JHEP* **08** (5, 2021) 080, [2105.07988]. 9

[207] V. Belavin, E. Trofimova and A. Ustyuzhanin, *Segmentation of EM showers for neutrino experiments with deep graph neural networks*, *JINST* **16** (4, 2021) P12035, [2104.02040]. 4

[208] A. Hariri, D. Dyachkova and S. Gleyzer, *Graph Generative Models for Fast Detector Simulations in High Energy Physics*, 2104.01725. 8

[209] Y. Verma and S. Jena, *Jet characterization in Heavy Ion Collisions by QCD-Aware Graph Neural Networks*, 2103.14906.

[210] G. Dezoort, S. Thais, I. Ojalvo, P. Elmer, V. Razavimaleki, J. Duarte et al., *Charged particle tracking via edge-classifying interaction networks*, *Comput.Softw.Big Sci.* **5** (3, 2021) 26, [2103.16701]. 4

[211] S. Thais and G. DeZoort, *Instance Segmentation GNNs for One-Shot Conformal Tracking at the LHC*, 3, 2021. 2103.06509. 4

[212] J. Hewes et al., *Graph Neural Network for Object Reconstruction in Liquid Argon Time Projection Chambers*, vol. 251, p. 03054, 3, 2021. 2103.06233. DOI. 4

[213] M. Rossi and S. Vallecorsa, *Deep Learning strategies for ProtoDUNE raw data denoising*, in *25th International Conference on Computing in High-Energy and Nuclear Physics*, vol. 6, p. 2, 3, 2021. 2103.01596. DOI. 4

[214] C. Biscarat, S. Caillou, C. Rougier, J. Stark and J. Zahreddine, *Towards a realistic track reconstruction algorithm based on graph neural networks for the HL-LHC*, in *25th International Conference on Computing in High-Energy and Nuclear Physics*, vol. 251, p. 03047, 3, 2021. 2103.00916. DOI. 4

[215] J. Pata, J. Duarte, J.-R. Vlimant, M. Pierini and M. Spiropulu, *MLPF: Efficient machine-learned particle-flow reconstruction using graph neural networks*, *Eur.Phys.J.C* **81** (1, 2021) 381, [2101.08578].

[216] Z. Qian et al., *Vertex and Energy Reconstruction in JUNO with Machine Learning Methods*, *Nucl.Instrum.Meth.A* **1010** (1, 2021) 165527, [2101.04839]. 4

[217] F. A. Dreyer and H. Qu, *Jet tagging in the Lund plane with graph networks*, 2012.08526. 3

[218] Y. Verma and S. Jena, *Particle Track Reconstruction using Geometric Deep Learning*, 2012.08515. 4

[219] A. Heintz et al., *Accelerated Charged Particle Tracking with Graph Neural Networks on FPGAs*, *34th Conference on Neural Information Processing Systems* (11, 2020) , [2012.01563]. 6

[220] Jun Guo and Jinmian Li and Tianjun Li, *The Boosted Higgs Jet Reconstruction via Graph Neural Network*, *Phys.Rev.D* **103** (2020) 116025, [2010.05464]. 3

[221] S. Alonso-Monsalve, D. Douqa, C. Jesus-Valls, T. Lux, S. Pina-Otey, F. Sanchez et al., *Graph neural network for 3D classification of ambiguities and optical crosstalk in scintillator-based neutrino detectors*, 2009.00688. 4

[222] N. Choma et al., *Track Seeding and Labelling with Embedded-space Graph Neural Networks*, 2007.00149. 4

[223] X. Ju and B. Nachman, *Supervised Jet Clustering with Graph Neural Networks for Lorentz Boosted Bosons*, *Phys. Rev. D* **102** (2020) 075014, [2008.06064]. 3

[224] Y. Iiyama et al., *Distance-Weighted Graph Neural Networks on FPGAs for Real-Time Particle Reconstruction in High Energy Physics*, *Front. Big Data* **3** (2020) 598927, [2008.03601]. 6

[225] E. Bernreuther, T. Finke, F. Kahlhoefer, M. Krämer and A. Mück, *Casting a graph net to catch dark showers*, 2006.08639. 3

[226] M. Abdughani, D. Wang, L. Wu, J. M. Yang and J. Zhao, *Probing triple Higgs coupling with machine learning at the LHC*, *Phys.Rev.D* **104** (5, 2020) 056003, [2005.11086].

[227] A. Chakraborty, S. H. Lim, M. M. Nojiri and M. Takeuchi, *Neural Network-based Top Tagger with Two-Point Energy Correlations and Geometry of Soft Emissions*, 2003.11787. 3

[228] F. A. Di Bello, S. Ganguly, E. Gross, M. Kado, M. Pitt, L. Santi et al., *Towards a Computer Vision Particle Flow*, *Eur. Phys. J. C* **81** (2021) 107, [2003.08863].

[229] A. Chakraborty, S. H. Lim and M. M. Nojiri, *Interpretable deep learning for two-prong jet classification with jet spectra*, *JHEP* **19** (2020) 135, [1904.02092]. 3

[230] S. R. Qasim, J. Kieseler, Y. Iiyama and M. Pierini, *Learning representations of irregular particle-detector geometry with distance-weighted graph networks*, *Eur. Phys. J. C* **79** (2019) 608, [1902.07987]. 4

[231] E. A. Moreno, O. Cerri, J. M. Duarte, H. B. Newman, T. Q. Nguyen, A. Periwal et al., *JEDI-net: a jet identification algorithm based on interaction networks*, *Eur. Phys. J. C* **80** (2020) 58, [1908.05318]. 3

[232] J. Ren, L. Wu and J. M. Yang, *Unveiling CP property of top-Higgs coupling with graph neural networks at the LHC*, *Phys. Lett. B* **802** (2020) 135198, [1901.05627].

[233] J. Arjona Martínez, O. Cerri, M. Pierini, M. Spiropulu and J.-R. Vlimant, *Pileup mitigation at the Large Hadron Collider with graph neural networks*, *Eur. Phys. J. Plus* **134** (2019) 333, [1810.07988]. 6

[234] M. Abdughani, J. Ren, L. Wu and J. M. Yang, *Probing stop pair production at the LHC with graph neural networks*, *JHEP* **08** (2019) 055, [1807.09088].

[235] X. Ju et al., *Graph Neural Networks for Particle Reconstruction in High Energy Physics detectors*, *33rd Annual Conference on Neural Information Processing Systems* (3, 2020) , [2003.11603]. 4

[236] I. Henrion, K. Cranmer, J. Bruna, K. Cho, J. Brehmer, G. Louppe et al., *Neural Message Passing for Jet Physics*, 2017. 2

[237] E. E. Robles, A. Yankelevich, W. Wu, J. Bian and P. Baldi, *Particle Hit Clustering and Identification Using Point Set Transformers in Liquid Argon Time Projection Chambers*, *JINST* **20** (4, 2025) P07030, [2504.08182]. 2, 4

[238] J. Liu et al., *Neutrino type identification for atmospheric neutrinos in a large homogeneous liquid scintillation detector*, *Phys.Rev.D* **112** (3, 2025) 012018, [2503.21353].

[239] N. S. Woodward, S. E. Park, G. Grosso, J. Krupa and P. Harris, *Product Manifold Machine Learning for Physics*, 2412.07033. 3, 7

[240] J. Y. Araz, V. Mikuni, F. Ringer, N. Sato, F. T. Acosta and R. Whitehill, *Point cloud-based diffusion models for the Electron-Ion Collider*, *Phys.Lett.B* **868** (10, 2024) 139694, [2410.22421]. 8

[241] M. Leigh, S. Klein, F. Charton, T. Golling, L. Heinrich, M. Kagan et al., *Is Tokenization Needed for Masked Particle Modelling?*, 2409.12589. 9

[242] R. Gambhir, A. Osathapan and J. Thaler, *Moments of Clarity: Streamlining Latent Spaces in Machine Learning using Moment Pooling*, *Phys.Rev.D* **110** (3, 2024) 074020, [2403.08854].

[243] P. Odagiu et al., *Sets are All You Need: Ultrafast Jet Classification on FPGAs for HL-LHC*, *Mach.Learn.Sci.Tech.* **5** (2, 2024) 035017, [2402.01876].

[244] A. Hammad, S. Moretti and M. Nojiri, *Multi-scale cross-attention transformer encoder for event classification*, *JHEP* **03** (12, 2023) 144, [2401.00452]. 3

[245] S. Mondal, G. Barone and A. Schmidt, *PAIReD jet: A multi-pronged resonance tagging strategy across all Lorentz boosts*, *JHEP* **09** (11, 2023) 128, [2311.11011].

[246] F. T. Acosta, B. Karki, P. Karande, A. Angerami, M. Arratia, K. Barish et al., *The Optimal use of Segmentation for Sampling Calorimeters*, *JINST* **19** (10, 2023) P06002, [2310.04442]. 6

[247] E. Buhmann, C. Ewen, D. A. Faroughy, T. Golling, G. Kasieczka, M. Leigh et al., *EPiC-ly Fast Particle Cloud Generation with Flow-Matching and Diffusion*, 2310.00049. 8

[248] A. Badea and J. Montejo Berlingen, *A data-driven and model-agnostic approach to solving combinatorial assignment problems in searches for new physics*, *Phys.Rev.D* **109** (9, 2023) L011702, [2309.05728]. 5

[249] B. Käch and I. Melzer-Pellmann, *Attention to Mean-Fields for Particle Cloud Generation*, 2305.15254. 5

[250] D. Athanasakos, A. J. Larkoski, J. Mulligan, M. Ploskon and F. Ringer, *Is infrared-collinear safe information all you need for jet classification?*, *JHEP* **07** (5, 2023) 257, [2305.08979]. 3

[251] P. Onyisi, D. Shen and J. Thaler, *Comparing Point Cloud Strategies for Collider Event Classification*, *Phys.Rev.D* **108** (12, 2022) 012001, [2212.10659].

[252] B. Käch, D. Krücker and I. Melzer-Pellmann, *Point Cloud Generation using Transformer Encoders and Normalising Flows*, 2211.13623. 8

[253] ATLAS Collaboration, *Deep Sets based Neural Networks for Impact Parameter Flavour Tagging in ATLAS*, Tech. Rep. ATL-PHYS-PUB-2020-014, CERN, Geneva, May, 2020. 3

[254] C. Shimmin, *Particle Convolution for High Energy Physics*, 7, 2021. 2107.02908.

[255] A. Shmakov, M. J. Fenton, T.-W. Ho, S.-C. Hsu, D. Whiteson and P. Baldi, *SPANet: Generalized Permutationless Set Assignment for Particle Physics using Symmetry Preserving Attention*, *SciPost Phys.* **12** (6, 2021) 178, [2106.03898].

[256] V. Mikuni and F. Canelli, *Point Cloud Transformers applied to Collider Physics*, *Mach.Learn.Sci.Tech.* **2** (2, 2021) 035027, [2102.05073].

[257] J. S. H. Lee, I. Park, I. J. Watson and S. Yang, *Zero-Permutation Jet-Parton Assignment using a Self-Attention Network*, *J.Korean Phys.Soc.* **84** (12, 2020) 427, [2012.03542].

[258] M. J. Fenton, A. Shmakov, T.-W. Ho, S.-C. Hsu, D. Whiteson and P. Baldi, *Permutationless Many-Jet Event Reconstruction with Symmetry Preserving Attention Networks*, *Phys.Rev.D* **105** (10, 2020) 112008, [2010.09206].

[259] M. J. Dolan and A. Ore, *Equivariant Energy Flow Networks for Jet Tagging*, *Phys. Rev. D* **103** (2021) 074022, [2012.00964]. 7

[260] J. Shlomi, S. Ganguly, E. Gross, K. Cranmer, Y. Lipman, H. Serviansky et al., *Secondary Vertex Finding in Jets with Neural Networks*, *Eur.Phys.J.C* **81** (8, 2020) 540, [2008.02831]. 4

[261] V. Mikuni and F. Canelli, *ABCNet: An attention-based method for particle tagging*, *Eur. Phys. J. Plus* **135** (2020) 463, [2001.05311].

[262] H. Qu and L. Gouskos, *ParticleNet: Jet Tagging via Particle Clouds*, *Phys. Rev. D* **101** (2020) 056019, [1902.08570].

[263] P. T. Komiske, E. M. Metodiev and J. Thaler, *Energy Flow Networks: Deep Sets for Particle Jets*, *JHEP* **01** (2019) 121, [1810.05165]. 2

[264] N. Mallick, H. Hassan and D. J. Kim, *Charm-hadron reconstruction through three body decay in hadronic collisions using Machine Learning*, 2504.18279. 3, 4

[265] H. Hassan, N. Mallick and D. J. Kim, *Machine Learning-Based b-Jet Tagging in pp Collisions at* $\sqrt{s} = 13$ *TeV*, 2504.18291. 3

[266] V. Vatellis, *Advancing Physics Data Analysis through Machine Learning and Physics-Informed Neural Networks*, 2410.14760. 7

[267] A. Hallin, G. Kasieczka, S. Kraml, A. Lessa, L. Moureaux, T. von Schwartz et al., *Universal New Physics Latent Space*, *Phys.Rev.D* **111** (7, 2024) 016006, [2407.20315].

[268] S. Farrell, M. Bergevin and A. Bernstein, *Physics-informed machine learning approaches to reactor antineutrino detection*, 2407.06139.

[269] A. Ramirez-Morales, A. Gutiérrez-Rodríguez, T. Cisneros-Pérez, H. Garcia-Tecocoatzi and A. Dávila-Rivera, *Exotic and physics-informed support vector machines for high energy physics*, 2407.03538.

[270] K. T. Matchev, K. Matcheva, P. Ramond and S. Verner, *Exploring the Truth and Beauty of Theory Landscapes with Machine Learning*, *Phys.Lett.B* **856** (1, 2024) 138941, [2401.11513].

[271] M. A. Diaz, G. Cerro, J. Chaplais, S. Dasmahapatra and S. Moretti, *JetLOV: Enhancing Jet Tree Tagging through Neural Network Learning of Optimal LundNet Variables*, in *37th Conference on Neural Information Processing Systems*, 11, 2023. 2311.14654.

[272] A. Romero and D. Whiteson, *Jet Rotational Metrics*, *JHEP* **08** (11, 2023) 049, [2311.06686].

[273] E. Witkowski and D. Whiteson, *Learning Broken Symmetries with Resimulation and Encouraged Invariance*, 2311.05952.

[274] J. M. Munoz, I. Batatia, C. Ortner and F. Romeo, *Retrieval of Boost Invariant Symbolic Observables via Feature Importance*, 2306.13496.

[275] A. J. Larkoski, D. Rathjens, J. Veatch and J. W. Walker, *Jet SIFT-ing: a new scale-invariant jet clustering algorithm for the substructure era*, *Phys.Rev.D* **108** (2, 2023) 016005, [2302.08609].

[276] T. Kishimoto, M. Morinaga, M. Saito and J. Tanaka, *Decay-aware neural network for event classification in collider physics*, 12, 2022. 2212.08759.

[277] C. Grojean, A. Paul and Z. Qian, *Resurrecting* $b\bar{b}h$ *with kinematic shapes*, *JHEP* **04** (11, 2020) 139, [2011.13945]. 5, 10

[278] A. Butter, G. Kasieczka, T. Plehn and M. Russell, *Deep-learned Top Tagging with a Lorentz Layer*, *SciPost Phys.* **5** (2018) 028, [1707.08966]. 3

[279] P. T. Komiske, E. M. Metodiev and J. Thaler, *Energy flow polynomials: A complete linear basis for jet substructure*, *JHEP* **04** (2018) 013, [1712.07124].

[280] K. Datta and A. J. Larkoski, *Novel Jet Observables from Machine Learning*, *JHEP* **03** (2018) 086, [1710.01305].

[281] K. Datta and A. Larkoski, *How Much Information is in a Jet?*, *JHEP* **06** (2017) 073, [1704.08249].

[282] K. Datta, A. Larkoski and B. Nachman, *Automating the Construction of Jet Observables with Machine Learning*, 1902.07180. 3

[283] J. Li, P. Li, B. Long and R. Zhang, *Jet Reconstruction with Mamba Networks in Collider Events*, 2506.18336. 3, 4

[284] R. Colyer and D. Duda, *Proposed measurement of longitudinally polarised vector bosons in WH and ZH production at Hadron colliders*, 2506.13002.

[285] C. Bose, A. Chakraborty, S. Chowdhury and S. Dutta, *Interplay of Traditional Methods and Machine Learning Algorithms for Tagging Boosted Objects*, 2408.01138.

[286] A. Bogatskiy, T. Hoffman, D. W. Miller, J. T. Offermann and X. Liu, *Explainable Equivariant Neural Networks for Particle Physics: PELICAN*, *JHEP* **03** (7, 2023) 113, [2307.16506]. 3, 7

[287] P. Baroň, J. Kvita, R. Přívara, J. Tomeček and R. Vodák, *Application of Machine Learning Based Top Quark and W Jet Tagging to Hadronic Four-Top Final States Induced by SM as well as BSM Processes*, in *16th International Workshop on Top Quark Physics*, 10, 2023. 2310.13009. 3

[288] M. Grossi, M. Incudini, M. Pellen and G. Pelliccioli, *Amplitude-assisted tagging of longitudinally polarised bosons using wide neural networks*, *Eur.Phys.J.C* **83** (6, 2023) 759, [2306.07726].

[289] J. A. Aguilar-Saavedra, E. Arganda, F. R. Joaquim, R. M. Sandá Seoane and J. F. Seabra, *Gradient Boosting MUST taggers for highly-boosted jets*, *Eur.Phys.J.Plus* **139** (5, 2023) 1019, [2305.04957]. 3

[290] A. Subba and R. K. Singh, *Role of polarizations and spin-spin correlations of W's in e-e+→W-W+ at s=250 GeV to probe anomalous W-W+Z/γ couplings*, *Phys. Rev. D* **107** (2023) 073004, [2212.12973].

[291] T. Kim and A. Martin, *A $W^{\pm}$ polarization analyzer from Deep Neural Networks*, 2102.05124.

[292] Y.-C. J. Chen, C.-W. Chiang, G. Cottin and D. Shih, *Boosted W and Z tagging with jet charge and deep learning*, *Phys. Rev. D* **101** (2020) 053001, [1908.08256].

[293] CMS Collaboration, *Identification of heavy, energetic, hadronically decaying particles using machine-learning techniques*, *JINST* **15** (2020) P06005, [2004.08262]. 3

[294] R. Tagami, T. Suehara and M. Ishino, *Application of Particle Transformer to quark flavor tagging in the ILC project*, *EPJ Web Conf.* **315** (10, 2024) 03011, [2410.11322]. 3

[295] C. K. Khosa and S. Marzani, *Higgs tagging with the Lund jet plane*, *Phys.Rev.D* **104** (5, 2021) 055043, [2105.03989].

[296] C. Jang, S.-K. Ko, Y.-K. Noh, J. Choi, J. Lim and T. J. Kim, *Learning to increase matching efficiency in identifying additional b-jets in the $t\bar{t}b\bar{b}$ process*, *Eur.Phys.J.Plus* **137** (3, 2021) 870, [2103.09129].

[297] M. Abbas, A. Khan, A. S. Qureshi and M. W. Khan, *Extracting Signals of Higgs Boson From Background Noise Using Deep Neural Networks*, 2010.08201.

[298] B. Tannenwald, C. Neu, A. Li, G. Buehlmann, A. Cuddeback, L. Hatfield et al., *Benchmarking Machine Learning Techniques with Di-Higgs Production at the LHC*, 2009.06754.

[299] E. A. Moreno, T. Q. Nguyen, J.-R. Vlimant, O. Cerri, H. B. Newman, A. Periwal et al., *Interaction networks for the identification of boosted $H \to b\bar{b}$ decays*, *Phys. Rev. D* **102** (2020) 012010, [1909.12285].

[300] K. Datta, A. Larkoski and B. Nachman, *Automating the Construction of Jet Observables with Machine Learning*, *Phys. Rev. D* **100** (2019) 095016, [1902.07180]. 3

[301] ATLAS Collaboration, *A continuous calibration of the ATLAS flavour-tagging classifiers via optimal transportation maps*, 2505.13063. 3, 5

[302] J. Geuskens, N. Gite, M. Krämer, V. Mikuni, A. Mück, B. Nachman et al., *The Fundamental Limit of Jet Tagging*, 11, 2024. 2411.02628.

[303] J. Brehmer, V. Bresó, P. de Haan, T. Plehn, H. Qu, J. Spinner et al., *A Lorentz-Equivariant Transformer for All of the LHC*, 2411.00446. 3, 7, 8

[304] Y. Wu, K. Wang and J. Zhu, *Jet Tagging with More-Interaction Particle Transformer*, 2407.08682.

[305] J. O. Sandoval, V. Manian and S. Malik, *A multicategory jet image classification framework using deep neural network*, 2407.03524.

[306] F. Blekman, F. Canelli, A. De Moor, K. Gautam, A. Ilg, A. Macchiolo et al., *Jet*

Flavour Tagging at FCC-ee with a Transformer-based Neural Network: DeepJetTransformer, *Eur.Phys.J.C* **85** (6, 2024) 165, [2406.08590].

[307] M. J. Dolan, J. Gargalionis and A. Ore, *Quark-versus-gluon tagging in CMS Open Data with CWoLa and TopicFlow*, *JHEP* **08** (12, 2023) 024, [2312.03434].

[308] W. Shen, D. Wang and J. M. Yang, *Hierarchical High-Point Energy Flow Network for Jet Tagging*, *JHEP* **09** (8, 2023) 135, [2308.08300]. 3

[309] M. He and D. Wang, *Quark/Gluon Discrimination and Top Tagging with Dual Attention Transformer*, *Eur.Phys.J.C* **83** (7, 2023) 1116, [2307.04723]. 3

[310] M. Crispim Romão, J. G. Milhano and M. van Leeuwen, *Jet substructure observables for jet quenching in Quark Gluon Plasma: a Machine Learning driven analysis*, *SciPost Phys.* **16** (4, 2023) 015, [2304.07196]. 4

[311] S. Bright-Thonney, I. Moult, B. Nachman and S. Prestel, *Systematic Quark/Gluon Identification with Ratios of Likelihoods*, *JHEP* **12** (7, 2022) 021, [2207.12411].

[312] F. Dreyer, G. Soyez and A. Takacs, *Quarks and gluons in the Lund plane*, *JHEP* **08** (12, 2021) 177, [2112.09140].

[313] A. Romero, D. Whiteson, M. Fenton, J. Collado and P. Baldi, *Safety of Quark/Gluon Jet Classification*, 2103.09103. 10

[314] J. S. H. Lee, S. M. Lee, Y. Lee, I. Park, I. J. Watson and S. Yang, *Quark Gluon Jet Discrimination with Weakly Supervised Learning*, *J. Korean Phys. Soc.* **75** (2019) 652–659, [2012.02540]. 5

[315] G. Kasieczka, S. Marzani, G. Soyez and G. Stagnitto, *Towards Machine Learning Analytics for Jet Substructure*, 2007.04319.

[316] G. Kasieczka, N. Kiefer, T. Plehn and J. M. Thompson, *Quark-Gluon Tagging: Machine Learning vs Detector*, *SciPost Phys.* **6** (2019) 069, [1812.09223].

[317] Y.-T. Chien and R. Kunnawalkam Elayavalli, *Probing heavy ion collisions using quark and gluon jet substructure*, 1803.03589. 4

[318] M. Stoye, J. Kieseler, M. Verzetti, H. Qu, L. Gouskos, A. Stakia et al., *DeepJet: Generic physics object based jet multiclass classification for LHC experiments*, 2017. 3

[319] S. Rai, Prisha and J. Kumar, *Investigating 1-Bit Quantization in Transformer-Based Top Tagging*, 2508.07431. 6

[320] ATLAS Collaboration, *Transforming jet flavour tagging at ATLAS*, 2505.19689. 3

[321] W. Esmail, A. Hammad and M. Nojiri, *IAFormer: Interaction-Aware Transformer network for collider data analysis*, 2505.03258. 5

[322] A. J. Larkoski, *Systematic Interpretability and the Likelihood for Boosted Top Quark Identification*, 2411.00104.

[323] J. Kvita, P. Baroň, M. Machalová, R. Přívara, R. Vodák and J. Tomeček, *Application of Machine Learning Based Top Quark and W Jet Tagging to Hadronic Four-Top Final States Induced by SM and BSM Processes*, 2410.13904.

[324] Z. Dong, D. Gonçalves, K. Kong, A. J. Larkoski and A. Navarro, *Hadronic Top Quark Polarimetry with ParticleNet*, *Phys.Lett.B* **862** (7, 2024) 139314, [2407.01663].

[325] T. Cai, J. Cheng, N. Craig, G. Koszegi and A. J. Larkoski, *The Phase Space Distance Between Collider Events*, *JHEP* **09** (5, 2024) 054, [2405.16698]. 5

[326] V. S. Ngairangbam and M. Spannowsky, *Interpretable deep learning models for the inference and classification of LHC data*, *JHEP* **05** (12, 2023) 004, [2312.12330]. 10

[327] A. Furuichi, S. H. Lim and M. M. Nojiri, *Jet Classification Using High-Level Features from Anatomy of Top Jets*, *JHEP* **07** (12, 2023) 146, [2312.11760].

[328] J. Batson and Y. Kahn, *Scaling Laws in Jet Classification*, *SciPost Phys.Core* **8** (12, 2023) 034, [2312.02264].

[329] R. Liu, A. Gandrakota, J. Ngadiuba, M. Spiropulu and J.-R. Vlimant, *Efficient and Robust Jet Tagging at the LHC with Knowledge Distillation*, in *37th Conference on Neural Information Processing Systems*, 11, 2023. 2311.14160.

[330] A. Bogatskiy, T. Hoffman and J. T. Offermann, *19 Parameters Is All You Need: Tiny Neural Networks for Particle Physics*, in *37th Conference on Neural Information Processing Systems*, 10, 2023. 2310.16121.

[331] R. Sahu and K. Ghosh, *ML-Based Top Taggers: Performance, Uncertainty and Impact of Tower & Tracker Data Integration*, *SciPost Phys.* **17** (9, 2023) 166, [2309.01568]. 9

[332] B. Işıldak, A. Hayreter, M. Hüdaverdi, F. Ilgın, S. Salva, E. Şimşek et al., *Investigating the Violation of Charge-parity Symmetry Through Top-quark ChromoElectric Dipole Moments by Using Machine Learning Techniques*, *Acta Phys. Polon. B* **54** (2023) 5–A4, [2306.11683].

[333] P. Keicher, *Machine Learning in Top Physics in the ATLAS and CMS Collaborations*, in *15th International Workshop on Top Quark Physics*, 1, 2023. 2301.09534.

[334] B. Bhattacherjee, C. Bose, A. Chakraborty and R. Sengupta, *Boosted top tagging and its interpretation using Shapley values*, *Eur.Phys.J.Plus* **139** (12, 2022) 1131, [2212.11606].

[335] J. M. Munoz, I. Batatia and C. Ortner, *BIP: Boost Invariant Polynomials for Efficient Jet Tagging*, *Mach.Learn.Sci.Tech.* **3** (7, 2022) 04LT05, [2207.08272].

[336] I. Ahmed, A. Zada, M. Waqas and M. U. Ashraf, *Application of deep learning in top pair and single top quark production at the LHC*, *Eur.Phys.J.Plus* **138** (3, 2022) 795, [2203.12871].

[337] F. A. Dreyer, R. Grabarczyk and P. F. Monni, *Leveraging universality of jet taggers through transfer learning*, *Eur.Phys.J.C* **82** (3, 2022) 564, [2203.06210].

[338] J. A. Aguilar-Saavedra, *Pulling the Higgs and Top needles from the jet stack with Feature Extended Supervised Tagging*, *Eur.Phys.J.C* **81** (2, 2021) 734, [2102.01667].

[339] S. H. Lim and M. M. Nojiri, *Morphology for Jet Classification*, *Phys.Rev.D* **105** (10, 2020) 014004, [2010.13469].

[340] S. Bhattacharya, M. Guchait and A. H. Vijay, *Boosted Top Quark Tagging and Polarization Measurement using Machine Learning*, *Phys.Rev.D* **105** (10, 2020) 042005, [2010.11778].

[341] S. Diefenbacher, H. Frost, G. Kasieczka, T. Plehn and J. M. Thompson, *CapsNets Continuing the Convolutional Quest*, *SciPost Phys.* **8** (2020) 023, [1906.11265]. 3, 10

[342] J. Heo, W. Jang, J. S. H. Lee, Y. J. Roh, I. J. Watson and S. Yang, *Improving the Direct Determination of $|V_{ts}|$ using Deep Learning*, 2502.02918. 3

[343] A. Greljo, H. Tiblom and A. Valenti, *New Physics Through Flavor Tagging at FCC-ee*, *SciPost Phys.* **18** (11, 2024) , [2411.02485].

[344] Y. Kats and E. Ofir, *From strange-quark tagging to fragmentation tagging with machine learning*, *Phys.Rev.D* **111** (8, 2024) 034003, [2408.12377].

[345] A. Subba and R. K. Singh, *Study of anomalous $W^-W^+\gamma/Z$ couplings using polarizations and spin correlations in $e^-e^+ \to W^-W^+$ with polarized beams*, *Eur.Phys.J.C* **83** (5, 2023) 1119, [2305.15106].

[346] J. Erdmann, O. Nackenhorst and S. V. Zeißner, *Maximum performance of strange-jet tagging at hadron colliders*, *JINST* **16** (11, 2020) 08, [2011.10736].

[347] J. Erdmann, *A tagger for strange jets based on tracking information using long short-term memory*, *JINST* **15** (2020) P01021, [1907.07505].

[348] Y. Nakai, D. Shih and S. Thomas, *Strange Jet Tagging*, 2003.09517. 3

[349] J. Song, *DNN-based identification of additional b jets for a differential $t\bar{t}b\bar{b}$ cross section measurement*, in *16th International Workshop on Top Quark Physics*, 1, 2024. 2401.07626. 3

[350] S. Van Stroud, N. Pond, M. Hart, J. Barr, S. Rettie, G. Facini et al., *Vertex Reconstruction with MaskFormers*, 2312.12272.

[351] N. Tamir, I. Bessudo, B. Chen, H. Raiko and L. Barak, *Neural networks for boosted di-τ identification*, *JINST* **19** (12, 2023) P07004, [2312.08276].

[352] ATLAS Collaboration, *Fast b-tagging at the high-level trigger of the ATLAS experiment in LHC Run 3*, *JINST* **18** (6, 2023) P11006, [2306.09738].

[353] A. Stein, *Improving robustness of jet tagging algorithms with adversarial training: exploring the loss surface*, in *21th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI meets Reality*, 3, 2023. 2303.14511.

[354] L. Liao, S. Wang, W. Song, Z. Zhang and G. Li, *Performance studies of jet flavor tagging and measurement of R_b using ParticleNet at CEPC*, *Int.J.Mod.Phys.A* **38** (8, 2022) 2350168, [2208.13503].

[355] J. Bielcikoaá, R. K. Elayavalli, G. Ponimatkin, J. H. Putschke and J. Sivic, *Identifying Heavy-Flavor Jets Using Vectors of Locally Aggregated Descriptors*, 2005.01842.

[356] T. Keck et al., *The Full Event Interpretation: An Exclusive Tagging Algorithm for the Belle II Experiment*, *Comput. Softw. Big Sci.* **3** (2019) 6, [1807.08680]. 4, 11

[357] CMS Collaboration, *Identification of heavy-flavour jets with the CMS detector in pp collisions at 13 TeV*, 1712.07158. 3

[358] S. Nishimura, C. Miyao and H. Otsuka, *Reinforcement learning-based statistical search strategy for an axion model from flavor*, 2409.10023. 3, 5

[359] M. Mansouri, K. Bitaghsir Fadafan and X. Chen, *Holographic complex potential of a quarkonium from deep learning*, 2406.06285.

[360] B. Chen, X. Chen, X. Li, Z.-R. Zhu and K. Zhou, *Exploring Transport Properties of Quark-Gluon Plasma with a Machine-Learning assisted Holographic Approach*, *Phys.Rev.D* **111** (4, 2024) 086033, [2404.18217].

[361] M. Malekhosseini, S. Rostami, A. R. Olamaei, R. Ostovar and K. Azizi, *Meson mass and width: Deep learning approach*, *Phys.Rev.D* **110** (3, 2024) 054011, [2404.00448].

[362] D. A. O. Co, V. A. A. Chavez and D. L. B. Sombillo, *A Deep Learning Framework for Disentangling Triangle Singularity and Pole-Based Enhancements*, *Phys.Rev.D* **110** (3, 2024) 114034, [2403.18265].

[363] W.-B. Chang and D.-f. Hou, *Heavy quarkonium spectral function in an anisotropic background*, *Phys. Rev. D* **109** (3, 2024) 086010, [2403.04966].

[364] Z. Tian, G. Zhao, L. Wu, Z. Zhang, X. Zhou, S. Xin et al., *Cluster Counting Algorithm for the CEPC Drift Chamber using LSTM and DGCNN*, *Nucl.Sci.Tech.* **36** (2, 2024) 113, [2402.16493].

[365] R. E. C. Smith, I. Ochoa, R. Inácio, J. Shoemaker and M. Kagan, *Differentiable Vertex Fitting for Jet Flavour Tagging*, *Phys.Rev.D* **110** (10, 2023) 052010, [2310.12804]. 10

[366] S. Nishimura, C. Miyao and H. Otsuka, *Exploring the flavor structure of quarks and leptons with reinforcement learning*, *JHEP* **12** (4, 2023) 021, [2304.14176]. 5

[367] Z. Zhang, J. Liu, J. Hu, Q. Wang and U.-G. Meißner, *Revealing the nature of hidden charm pentaquarks with machine learning*, 2301.05364.

[368] H. Bahtiyar, *Predicting Exotic Hadron Masses with Data Augmentation Using Multilayer Perceptron*, *Int.J.Mod.Phys.A* **38** (8, 2022) 2350003, [2208.09538].

[369] S. Bhattacharya, S. Nandi, S. K. Patra and S. Sahoo, *'Deep' Dive into $b \to c$ Anomalies: Standardized and Future-proof Model Selection Using Self-normalizing Neural Networks*, 2008.04316. 3

[370] B. Fuks, S. K. Garg, A. Hammad and A. Jueid, *Deep learning approaches to top FCNC couplings to photons at the LHC*, 2507.17807. 3, 5

[371] H. Taha, E.-s. A. El-dahshan and S. Elgammal, *Search for a Dark Gauge Boson Within Einstein-Cartan Theory at the ILC Using Multivariate Analysis*, 2507.08678.

[372] Y. Dong, M. Ruan, K. Wang, H. Yang and J. Zhu, *Testing a 95 GeV Scalar at the CEPC with Machine Learning*, 2506.21454.

[373] T. Flacke, J. H. Kim, M. Kunkel, J. S. Pi and W. Porod, *Hunting and identifying coloured resonances in four top events with machine learning*, 2506.04318.

[374] J. Bardhan, T. Mandal, S. Mitra, C. Neeraj and M. Rawat, *Tagging fully hadronic exotic decays of the vectorlike* **B** *quark using a graph neural network*, *Phys.Rev.D* **112** (5, 2025) 1, [2505.07769].

[375] S.-Y. Chen, Y.-P. Jiao, S.-Y. Wang, Q.-S. Yan, H.-H. Zhang and Y. Zhang, *Heavy neutrino mixing prospects at hadron colliders: a machine learning study*, 2504.12141.

[376] N. Batra, B. Coleppa, A. Khanna, S. K. Rai and A. Sarkar, *Constraining the 3HDM Parameter Space*, *Phys.Rev.D* **112** (4, 2025) 015011, [2504.07489].

[377] M. G. Bostanabad and M. Mohammadi Najafabadi, *Machine Learning Approaches to Top Quark Flavor-Changing Four-Fermion Interactions in Trilepton Signals at the LHC*, *Phys.Rev.D* **111** (2, 2025) 11, [2502.18667].

[378] B. Ko, J. Heo, W. Jang, J. S. H. Lee, Y. J. Roh, I. J. Watson et al., *Identification of tqg flavor-changing neutral current interactions using machine learning techniques*, *J. Korean Phys. Soc.* **86** (2025) 269–279, [2502.04844].

[379] E. Abasov et al., *Separation of left-handed and anomalous right-handed vector operators contributions into the Wtb vertex for single and double resonant top quark production processes using a neural network*, *Phys.Part.Nucl.* **56** (12, 2024) 447, [2412.02468].

[380] E. Richter-Was, T. Yerniyazov and Z. Was, *Pseudo-observables and Deep Neural Network for mixed CP – H to tau tau decays at LHC*, 2411.06216.

[381] A. S. Cornell, B. Fuks, M. D. Goodsell and A. M. Ncube, *Improving smuon searches with Neural Networks*, *Eur.Phys.J.C* **85** (11, 2024) 51, [2411.04526].

[382] E. Arganda, M. Carena, M. de los Rios, A. D. Perez, D. Rocha, R. M. Sandá Seoane et al., *Machine-Learning Analysis of Radiative Decays to Dark Matter at the LHC*, *JHEP* **07** (10, 2024) 014, [2410.13799].

[383] S. Verma, S. Biswas, T. Mandal and S. Mitra, *Machine learning tagged boosted dark photon: A signature of fermionic portal matter at the LHC*, 2410.06925.

[384] G. Grosso and M. Letizia, *Multiple testing for signal-agnostic searches of new physics with machine learning*, *Eur.Phys.J.C* **85** (8, 2024) 4, [2408.12296].

[385] G. N. Wojcik, S. T. Eu and L. L. Everett, *Graph Reinforcement Learning for Exploring BSM Model Spaces*, *Phys.Rev.D* **111** (7, 2024) 035007, [2407.07203].

[386] G. Bickendorf and M. Drees, *Learning to see R-parity violating scalar top decays*, *Phys.Rev.D* **110** (6, 2024) 056006, [2406.03096].

[387] W. Esmail, A. Hammad, A. Jueid and S. Moretti, *Boosting probes of CP violation in the top Yukawa coupling with Deep Learning*, 2405.16499.

[388] I. Ahmed, U. Ahmad, J. Muhammad and S. Shafaq, *Leptoquark Searches at TeV Scale Using Neural Networks at Hadron Collider*, 2405.08090.

[389] C.-W. Chiang, F.-Y. Hsieh, S.-C. Hsu and I. Low, *Deep Learning to Improve the Sensitivity of Di-Higgs Searches in the 4b Channel*, *JHEP* **09** (1, 2024) 139, [2401.14198].

[390] D. Jurčiukonis, *Machine Learning for Prediction of Unitarity and Bounded from Below Constraints*, *PoS* **EPS-HEP2023** (2024) 494, [2401.09130].

[391] Y. Ma, A. Arhrib, S. Moretti, S. Semlali, Y. Wang and Q. S. Yan, *Analysis of the $gg \to H \to hh \to 4\tau$ process in the 2HDM lepton specific model at the LHC*, 2401.07289.

[392] Y. Zhang, C. Mo, X. Chen, B. Li, H. Chen, J. Hu et al., *Search for Long-lived Particles at Future Lepton Colliders Using Deep Learning Techniques*, 2401.05094.

[393] A. Hammad, K. Kong, M. Park and S. Shim, *Quantum Metric Learning for New Physics Searches at the LHC*, 2311.16866. 5

[394] S. Zhang, Y.-C. Guo and J.-C. Yang, *Optimize the event selection strategy the study the anomalous quartic gauge couplings at muon colliders using the support vector machine*, *Eur.Phys.J.C* **84** (11, 2023) 833, [2311.15280].

[395] D. Wang, J.-H. Cho, J. Kim, S. Lee, P. Sanyal and J. Song, *Probing Light Fermiophobic Higgs Boson via diphoton jets at the HL-LHC*, *Phys.Rev.D* **109** (10, 2023) 015017, [2310.17741].

[396] A. S. Grefsrud, T. Buanes, F. Koutroulis, A. Lipniacka, R. Maselek, A. Papaefstathiou et al., *Machine Learning Classification of Sphalerons and Black Holes at the LHC*, *Eur.Phys.J.C* **84** (10, 2023) 442, [2310.15227].

[397] A. Choudhury, A. Mondal, S. Mondal and S. Sarkar, *Improving sensitivity of trilinear RPV SUSY searches using machine learning at the LHC*, *Phys.Rev.D* **109** (8, 2023) 035001, [2308.02697].

[398] W. Esmail, A. Hammad and S. Moretti, *Sharpening the $A \to Z^{(*)}h$ Signature of the Type-II 2HDM at the LHC through Advanced Machine Learning*, *JHEP* **11** (5, 2023) 020, [2305.13781].

[399] L. Cremer, J. Erdmann, R. Harnik, J. L. Späh and E. Stamou, *Leveraging on-shell interference to search for FCNCs of the top quark and the Z boson*, *Eur.Phys.J.C* **83** (5, 2023) 871, [2305.12172].

[400] D. Bardhan, Y. Kats and N. Wunch, *Searching for dark jets with displaced vertices using weakly supervised machine learning*, *Phys.Rev.D* **108** (5, 2023) 035036, [2305.04372]. 5

[401] T. Flacke, J. H. Kim, M. Kunkel, P. Ko, J. S. Pi, W. Porod et al., *Uncovering doubly charged scalars with dominant three-body decays using machine learning*, *JHEP* **11** (4, 2023) 009, [2304.09195].

[402] C.-T. Lu, H. Lv, W. Shen, L. Wu and J. Zhang, *Probing Dark QCD Sector through the Higgs Portal with Machine Learning at the LHC*, *JHEP* **08** (4, 2023) 187, [2304.03237].

[403] Q. Guo, L. Gao, Y. Mao and Q. Li, *Search for vector-like leptons at a Muon Collider*, *Chin.Phys.C* **47** (4, 2023) 103106, [2304.01885].

[404] Y.-F. Dong, Y.-C. Mao and J.-C. Yang, *Searching for anomalous quartic gauge couplings at muon colliders using principle component analysis*, *Eur.Phys.J.C* **83** (4, 2023) 555, [2304.01505].

[405] V. K. MB, A. K. Nayak and A. K. Radhakrishnan, *Invariant mass reconstruction of heavy gauge bosons decaying to τ leptons using machine learning techniques*, *Eur.Phys.J.C* **84** (4, 2023) 219, [2304.01126].

[406] K. Pedro and P. Shyamsundar, *Optimal Mass Variables for Semivisible Jets*, *SciPost Phys.Core* **6** (3, 2023) 067, [2303.16253].

[407] W. Liu, J. Li, Z. Chen and H. Sun, *Probing Heavy Neutrinos at the LHC from Fat-jet using Machine Learning*, 2303.15920.

[408] P. Palit and S. Shil, *Probing Electroweak Phase Transition in Singlet scalar extension of Standard Model at HL-LHC through $bbZZ$ channel using parameterized machine learning*, *J.Phys.G* **51** (2, 2023) 095005, [2302.04191].

[409] ATLAS Collaboration, *Search for a new scalar resonance in flavour-changing neutral-current top-quark decays $t \to qX$ $(q = u, c)$, with $X \to b\bar{b}$, in proton-proton collisions at $\sqrt{s} = 13$ TeV with the ATLAS detector*, *JHEP* **07** (2023) 199, [2301.03902]. 11

[410] E. Ballabene, *Search for Electroweak Production of Supersymmetric Particles in Compressed Mass Spectra With the ATLAS Detector at the LHC*. PhD thesis, Milan U., U. Milan (main), 2022. 2211.11642.

[411] CMS Collaboration, *Search for supersymmetry in final states with a single electron or muon using angular correlations and heavy-object identification in proton-proton collisions at $\sqrt{s}$ = 13 TeV*, *JHEP* **09** (11, 2022) 149, [2211.08476]. 11

[412] ATLAS Collaboration, *Search for supersymmetry in final states with missing transverse momentum and three or more b-jets in 139 fb^{-1} of proton–proton collisions at $\sqrt{s} = 13$ TeV with the ATLAS detector*, *Eur. Phys. J. C* **83** (2023) 561, [2211.08028]. 11

[413] G. Bhattacharyya, I. Chakraborty, D. K. Ghosh, T. Jha and G. Saha, *Searching for exotic Higgs bosons from top quark decays at the HL-LHC*, *Eur.Phys.J.C* **84** (12, 2022) 927, [2212.09061].

[414] J. Bardhan, T. Mandal, S. Mitra and C. Neeraj, *Machine learning-enhanced search for a vectorlike-singlet* **B** *quark decaying to a singlet scalar or pseudoscalar*, *Phys.Rev.D* **107** (12, 2022) 115001, [2212.02442].

[415] S. Bhattacharya, S. Biswas, K. Pal and J. Wudka, *Associated production of Higgs and single top at the LHC in presence of the SMEFT operators*, *JHEP* **08** (11, 2022) 015, [2211.05450].

[416] T. Faucett, S.-C. Hsu and D. Whiteson, *Learning to Identify Semi-Visible Jets*, *JHEP* **12** (8, 2022) 132, [2208.10062].

[417] N. C. Hall, I. Criddle, A. Crossland, C. Englert, P. Forbes, R. Hankache et al., *Machine-enhanced CP-asymmetries in the electroweak sector*, *Phys.Rev.D* **107** (9, 2022) 016008, [2209.05143].

[418] C.-W. Chiang, D. Shih and S.-F. Wei, *VBF vs. GGF Higgs with Full-Event Deep*

Learning: Towards a Decay-Agnostic Tagger, *Phys.Rev.D* **107** (9, 2022) 016014, [2209.05518].

[419] D. Barbosa, F. Díaz, L. Quintero, A. Flórez, M. Sanchez, A. Gurrola et al., *Probing a Z′ with non-universal fermion couplings through top quark fusion, decays to bottom quarks, and machine learning techniques*, *Eur.Phys.J.C* **83** (10, 2022) 413, [2210.15813].

[420] L. Alasfar, R. Gröber, C. Grojean, A. Paul and Z. Qian, *Machine learning the trilinear and light-quark Yukawa couplings from Higgs pair kinematic shapes*, *JHEP* **11** (7, 2022) 045, [2207.04157].

[421] J.-C. Yang, X.-Y. Han, Z.-B. Qin, T. Li and Y.-C. Guo, *Measuring the anomalous quartic gauge couplings in the $W^+W^- \to W^+W^-$ process at muon collider using artificial neural networks*, *JHEP* **09** (4, 2022) 074, [2204.10034].

[422] X. Ai, S.-C. Hsu, K. Li and C.-T. Lu, *Probing highly collimated photon-jets with deep learning*, *J.Phys.Conf.Ser.* **2438** (3, 2022) 012114, [2203.16703].

[423] H. Lv, D. Wang and L. Wu, *Deep Learning Jet Image as a Probe of Light Higgsino Dark Matter at the LHC*, *Phys.Rev.D* **106** (3, 2022) 055008, [2203.14569].

[424] M. D. Goodsell and A. Joury, *Active learning BSM parameter spaces*, *Eur.Phys.J.C* **83** (4, 2022) 268, [2204.13950].

[425] F. F. Freitas, J. a. Gonçalves, A. P. Morais and R. Pasechnik, *Phenomenology at the Large Hadron Collider with Deep Learning: the case of vector-like quarks decaying to light jets*, *Eur.Phys.J.C* **82** (4, 2022) 826, [2204.12542].

[426] A. Badea, W. J. Fawcett, J. Huth, T. J. Khoo, R. Poggi and L. Lee, *Solving Combinatorial Problems at Particle Colliders Using Machine Learning*, *Phys.Rev.D* **106** (1, 2022) 016001, [2201.02205].

[427] P. Konar and V. S. Ngairangbam, *Influence of QCD parton shower in deep learning invisible Higgs through vector boson fusion*, *Phys.Rev.D* **105** (1, 2022) 113003, [2201.01040].

[428] J. Feng, M. Li, Q.-S. Yan, Y.-P. Zeng, H.-H. Zhang, Y. Zhang et al., *Improving heavy Dirac neutrino prospects at future hadron colliders using machine learning*, *JHEP* **09** (12, 2021) 141, [2112.15312].

[429] H. Beauchesne and G. G. di Cortona, *Event-level variables for semivisible jets using anomalous jet tagging*, in *2022 Snowmass Summer Study*, 11, 2021. 2111.12156.

[430] X. C. Vidal, L. D. Maroñas and A. D. Suárez, *How to use Machine Learning to improve the discrimination between signal and background at particle colliders*, *Appl.Sciences* **11** (10, 2021) 11076, [2110.15099].

[431] A. S. Cornell, W. Doorsamy, B. Fuks, G. Harmsen and L. Mason, *Boosted decision trees in the era of new physics: a smuon analysis case study*, *JHEP* **04** (9, 2021) 015, [2109.11815].

[432] M. Drees, M. Shi and Z. Zhang, *Machine Learning Optimized Search for the Z' from $U(1)_{L_\mu - L_\tau}$ at the LHC*, 2109.07674.

[433] S. Jung, Z. Liu, L.-T. Wang and K.-P. Xie, *Probing Higgs exotic decay at the LHC with machine learning*, *Phys.Rev.D* **105** (9, 2021) 035008, [2109.03294].

[434] A. P. Morais, A. Onofre, F. F. Freitas, J. a. Gonçalves, R. Pasechnik and R. Santos, *Deep Learning Searches for Vector-Like Leptons at the LHC and Electron/Muon Colliders*, *Eur.Phys.J.C* **83** (8, 2021) 232, [2108.03926].

[435] D. Alvestad, N. Fomin, J. Kersten, S. Maeland and I. Strümke, *Beyond Cuts in Small Signal Scenarios - Enhanced Sneutrino Detectability Using Machine Learning*, *Eur.Phys.J.C* **83** (8, 2021) 379, [2108.03125].

[436] J.-C. Yang, J.-H. Chen and Y.-C. Guo, *Extract the energy scale of anomalous $\gamma\gamma \to W^+W^-$ scattering in the vector boson scattering process using artificial neural networks*, *JHEP* **09** (7, 2021) 085, [2107.13624].

[437] J. Barron, D. Curtin, G. Kasieczka, T. Plehn and A. Spourdalakis, *Unsupervised Hadronic SUEP at the LHC*, *JHEP* **12** (7, 2021) 129, [2107.12379].

[438] J. Ren, D. Wang, L. Wu, J. M. Yang and M. Zhang, *Detecting an axion-like particle with machine learning at the LHC*, *JHEP* **11** (6, 2021) 138, [2106.07018].

[439] F. Jorge, R. Ronald, S. Jesus, M. Juan and A. Carlos, *Top squark signal significance enhancement by different Machine Learning Algorithms*, *Int.J.Mod.Phys.A* **37** (6, 2021) 2250197, [2106.06813].

[440] E. Arganda, A. D. Medina, A. D. Perez and A. Szynkman, *Towards a method to anticipate dark matter signals with deep learning at the LHC*, *SciPost Phys.* **12** (5, 2021) 063, [2105.12018].

[441] A. Stakia et al., *Advanced Multi-Variate Analysis Methods for New Physics Searches at the Large Hadron Collider*, *Rev.Phys.* **7** (5, 2021) 100063, [2105.07530].

[442] F. F. Freitas, C. K. Khosa and V. Sanz, *Exploring the standard model EFT in VH production with machine learning*, *Phys. Rev. D* **100** (2019) 035040, [1902.05803].

[443] C. K. Khosa, V. Sanz and M. Soughton, *WIMPs or else? Using Machine Learning to disentangle LHC signatures*, *SciPost Phys.* **10** (10, 2019) 151, [1910.06058].

[444] F. F. Freitas, J. a. Gonçalves, A. P. Morais and R. Pasechnik, *Phenomenology of vector-like leptons with Deep Learning at the Large Hadron Collider*, 2010.01307.

[445] C. Englert, M. Fairbairn, M. Spannowsky, P. Stylianou and S. Varma, *Sensing Higgs cascade decays through memory*, 2008.08611.

[446] V. S. Ngairangbam, A. Bhardwaj, P. Konar and A. K. Nayak, *Invisible Higgs search through Vector Boson Fusion: A deep learning approach*, 2008.05434.

[447] M. Grossi, J. Novak, D. Rebuzzi and B. Kersevan, *Comparing Traditional and Deep-Learning Techniques of Kinematic Reconstruction for polarisation Discrimination in Vector Boson Scattering*, 2008.05316.

[448] D. Cogollo, F. Freitas, C. S. Pires, Y. M. Oviedo-Torres and P. Vasconcelos, *Deep learnig analysis of the inverse seesaw in a 3-3-1 model at the LHC*, 2008.03409.

[449] S. Chang, T.-K. Chen and C.-W. Chiang, *Distinguishing W' Signals at Hadron Colliders Using Neural Networks*, 2007.14586.

[450] J. Alimena, Y. Iiyama and J. Kieseler, *Fast convolutional neural networks for identifying long-lived particles in a high-granularity calorimeter*, 2004.10744. 6

[451] C. Collaboration, *A deep neural network to search for new long-lived particles decaying to jets*, *Machine Learning: Science and Technology* (2020) , [1912.12238]. 7

[452] P. Baldi, P. Sadowski and D. Whiteson, *Searching for Exotic Particles in High-Energy Physics with Deep Learning*, *Nature Commun.* **5** (2014) 4308, [1402.4735]. 3

[453] J. E. Muñoz Méndez et al., *ML-based muon identification using a FNAL-NICADD scintillator chamber for the MID subsystem of ALICE 3*, 2507.02817. 4

[454] M. Chadeeva, P. Rogozhin and T. Uglov, *Performance of the FARICH-based particle identification at charm superfactories using machine learning*, 2506.14247.

[455] E. Habjan, R. Dube, J. McIntyre, M. Edo and R. Jones, *Particle identification in the GlueX detector using a multi-layer perceptron*, 2505.14706.

[456] O. M. Khalaf and A. M. Hamed, *Deep Neural Networks for Cross-Energy Particle Identification at RHIC and LHC*, 2505.06732. 10

[457] KM3NeT Collaboration, *Measurement of the atmospheric ν_μ flux with six detection units of KM3NeT/ORCA*, *Eur.Phys.J.C* **85** (4, 2025) 871, [2504.09119]. 4

[458] KM3NeT Collaboration, *Reconstruction of muon bundles in KM3NeT detectors using machine learning methods*, 3, 2025. 2503.01433. 4

[459] A. Hammad and M. M. Nojiri, *Transformer networks for Heavy flavor jet tagging*, *J.Phys.Soc.Jap.* **94** (11, 2024) 031007, [2411.11519].

[460] S. Van Stroud, P. Duckett, M. Hart, N. Pond, S. Rettie, G. Facini et al., *Transformers for Charged Particle Track Reconstruction in High Energy Physics*, 2411.07149.

[461] X. Ai, W. Y. Feng, S.-C. Hsu, K. Li and C.-T. Lu, *Detecting highly collimated photon-jets from Higgs boson exotic decays with deep learning*, 2401.15690.

[462] M. Kasak, K. Deja, M. Karwowska, M. Jakubowska, L. Graczykowski and M. Janik, *Machine-learning-based particle identification with missing data*, *Eur.Phys.J.C* **84** (12, 2023) 691, [2401.01905].

[463] S. Song, J. Chen, J. Liu, Y. Liu, B. Qi, Y. Shi et al., *Study of residual artificial neural network for particle identification in the CEPC high-granularity calorimeter prototype*, *JINST* **19** (10, 2023) P04033, [2310.09489].

[464] ALICE collaboration, M. Karwowska, M. Jakubowska, L. Graczykowski, K. Deja and M. Kasak, *Particle identification with machine learning in ALICE Run 3*, in *26th International Conference on Computing in High Energy & Nuclear Physics*, vol. 295, p. 09029, 9, 2023. 2309.07768. DOI.

[465] NA62 Collaboration, *Improved calorimetric particle identification in NA62 using machine learning techniques*, *JHEP* **11** (4, 2023) 138, [2304.10580].

[466] A. N. Charan, *Particle identification with the Belle II calorimeter using machine learning*, *J. Phys. Conf. Ser.* **2438** (2023) 012111, [2301.11654].

[467] A. Novosel, A. N. Charan, L. Šantelj, T. Ferber, P. Križan and B. Golob, *Identification of light leptons and pions in the electromagnetic calorimeter of Belle II*, in *11th International Workshop on Ring Imaging Cherenkov Detectors* , vol. 1056, p. 168630, 1, 2023. 2301.05074. DOI.

[468] T. Lange, S. Nandan, J. Pata, L. Tani and C. Veelken, *Particle-flow based tau identification at future e^+e^- colliders*, *Comput.Phys.Commun.* **298** (7, 2023) 109095, [2307.07747].

[469] S. Prasad, N. Mallick and R. Sahoo, *Inclusive, prompt and non-prompt* J/ψ *identification in proton-proton collisions at the Large Hadron Collider using machine learning*, *Phys.Rev.D* **109** (8, 2023) 014005, [2308.00329].

[470] H. Wu et al., *Machine learning method for* ^{12}C *event classification and reconstruction in the active target time-projection chamber*, *Nucl.Instrum.Meth.A* **1055** (4, 2023) 168528, [2304.13233].

[471] N. Kushawaha, Y. Furletova, A. Roy and D. Romanov, *Separation of electrons from pions in GEM TRD using deep learning*, 2303.10776.

[472] LHCb collaboration, A. Ryzhikov, A. Temirkhanov, D. Derkach, M. Hushchyn, N. Kazeev and S. Mokhnenko, *Robust Neural Particle Identification Models*, *J. Phys. Conf. Ser.* **2438** (2023) 012119, [2212.07274].

[473] PADME collaboration, K. Dimitrova, *Using Artificial Intelligence in the*

Reconstruction of Signals from the PADME Electromagnetic Calorimeter, *Instruments* **6** (2022) 46, [2210.00811].

[474] C. Fanelli and A. Mahmood, *Artificial Intelligence for Imaging Cherenkov Detectors at the EIC*, in *Experimental Applications of Artificial Intelligence for the Electron Ion Collider*, vol. 17, p. C07011, 4, 2022. 2204.08645. DOI.

[475] ALICE collaboration, L. K. Graczykowski, M. Jakubowska, K. R. Deja and M. Kabus, *Using Machine Learning for Particle Identification in ALICE*, vol. 17, p. C07016, 4, 2022. 2204.06900. DOI.

[476] G. Graziani, L. Anderlini, S. Mariani, E. Franzoso, L. Pappalardo and P. di Nezza, *A Neural-Network-defined Gaussian Mixture Model for particle identification applied to the LHCb fixed-target programme*, *JINST* **17** (10, 2021) P02018, [2110.10259]. 8

[477] Y. Verma and S. Jena, *Shower Identification in Calorimeter using Deep Learning*, 2103.16247.

[478] J. Collado, J. N. Howard, T. Faucett, T. Tong, P. Baldi and D. Whiteson, *Learning to Identify Electrons*, *Phys.Rev.D* **103** (11, 2020) 116028, [2011.01984].

[479] D. Belayneh et al., *Calorimetry with Deep Learning: Particle Simulation and Reconstruction for Collider Physics*, 1912.06794. 8

[480] B. Hooberman, A. Farbin, G. Khattak, V. Pacela, M. Pierini, J.-R. Vlimant et al., *Calorimetry with Deep Learning: Particle Classification, Energy Regression, and Simulation for High-Energy Physics*, 2017. 6, 8

[481] M. Paganini, L. de Oliveira and B. Nachman, *Survey of Machine Learning Techniques for High Energy Electromagnetic Shower Classification*, 2017.

[482] L. De Oliveira, B. Nachman and M. Paganini, *Electromagnetic Showers Beyond Shower Shapes*, *Nucl. Instrum. Meth. A* **951** (2020) 162879, [1806.05667]. 4

[483] A. Gavrikov et al., *Simulation-based inference for Precision Neutrino Physics through Neural Monte Carlo tuning*, 2507.23297. 4, 10

[484] P. Rodriguez-Grasa, P. Zhelnin, C. A. Argüelles and M. Sanz, *Neutrino Telescope Event Classification on Quantum Computers*, 2506.16530. 5

[485] C. Duffy, M. Jastrzebski, S. Vergani, L. H. Whitehead, R. Cross, A. Blake et al., *LArTPC hit-based topology classification with quantum machine learning and symmetry*, 2503.12655. 5

[486] A. Wilkinson, R. Radev and S. Alonso-Monsalve, *Contrastive Learning for Robust Representations of Neutrino Data*, *Phys.Rev.D* **111** (2, 2025) 092011, [2502.07724].

[487] DUNE Collaboration, *Neutrino Interaction Vertex Reconstruction in DUNE with Pandora Deep Learning*, *Eur.Phys.J.C* **85** (2, 2025) 697, [2502.06637].

[488] D. C. Hackett, J. Isaacson, S. W. Li, K. Tame-Narvaez and M. L. Wagman, *Machine Learning Neutrino-Nucleus Cross Sections*, 2412.16303.

[489] B. Kriesten and T. J. Hobbs, *Anomalous electroweak physics unraveled via evidential deep learning*, 2412.16286. 11

[490] E. León et al., *Machine Learning-Powered Data Cleaning for LEGEND*, *Mach.Learn.Sci.Tech.* **6** (10, 2024) 015064, [2410.14701].

[491] F. J. Yu, N. Kamp and C. A. Argüelles, *Learning Efficient Representations of Neutrino Telescope Events*, 2410.13148. 6

[492] A. Migala, E. Ku, Z. Li and A. Li, *Real-time Position Reconstruction for the KamLAND-Zen Experiment using Hardware-AI Co-design*, 2410.02991. 6

[493] F. J. Yu, N. Kamp and C. A. Argüelles, *Enhancing Events in Neutrino Telescopes through Deep Learning-Driven Super-Resolution*, *Phys.Rev.D* **111** (8, 2024) L041301, [2408.08474].

[494] J. Kopp, P. Machado, M. MacMahon and I. Martinez-Soler, *Improving Neutrino Energy Reconstruction with Machine Learning*, 2405.15867.

[495] C. Cai et al., *RELICS: a REactor neutrino LIquid xenon Coherent elastic Scattering experiment*, *Phys.Rev.D* **110** (5, 2024) 072011, [2405.05554].

[496] IceCube Collaboration, *Measurement of atmospheric neutrino oscillation parameters using convolutional neural networks with 9.3 years of data in IceCube DeepCore*, *Phys.Rev.Lett.* **134** (5, 2024) 091801, [2405.02163].

[497] A. Bat, *Using machine learning to separate Cherenkov and scintillation light in hybrid neutrino detector*, *JINST* **19** (2024) P04027, [2403.05184].

[498] F. J. Yu, J. Lazar and C. A. Arguelles-Delgado, *Trigger-Level Event Reconstruction for Neutrino Telescopes Using Sparse Submanifold Convolutional Neural Networks*, *PoS* **ICRC2023** (2023) 1004, [2303.08812].

[499] M. Biassoni, A. Giachero, M. Grossi, D. Guffanti, D. Labranca, R. Moretti et al., *Assessment of few-hits machine learning classification algorithms for low energy physics in liquid argon detectors*, *Eur.Phys.J.Plus* **139** (5, 2023) 723, [2305.09744]. 4, 5

[500] L. Bai, Y.-n. Mao and K. Wang, *Probing the mixing parameter |VτN|2 for heavy neutrinos*, *Phys. Rev. D* **107** (2023) 095008, [2211.00309].

[501] IceCube Collaboration, *Graph Neural Networks for low-energy event classification & reconstruction in IceCube*, *JINST* **17** (2022) P11003, [2209.03042].

[502] A. Søgaard, R. F. Ørsøe, L. Bozianu, M. Holm, K. E. Iversen, T. Guggenmos et al.,

GraphNeT: Graph neural networks for neutrino telescope event reconstruction, *J.Open Source Softw.* **8** (10, 2022) 4971, [2210.12194].

[503] M. Bachlechner, T. Birkenfeld, P. Soldin, A. Stahl and C. Wiebusch, *Partition Pooling for Convolutional Graph Network Applications in Particle Physics*, *JINST* **17** (8, 2022) P10004, [2208.05952].

[504] A. Chappell and L. H. Whitehead, *Application of Transfer Learning to Neutrino Interaction Classification*, *Eur. Phys. J. C* **82** (2022) 1099, [2207.03139].

[505] P. Lutkus, T. Wongjirad and S. Aeron, *Towards Designing and Exploiting Generative Networks for Neutrino Physics Experiments using Liquid Argon Time Projection Chambers*, in *9th International Conference on Learning Representations*, 4, 2022. 2204.02496.

[506] DUNE Collaboration, *Separation of track- and shower-like energy deposits in ProtoDUNE-SP using a convolutional neural network*, *Eur.Phys.J.C* **82** (3, 2022) 903, [2203.17053].

[507] Z. A. Elkarghli, *Improvement of the NOvA Near Detector Event Reconstruction and Primary Vertexing through the Application of Machine Learning Methods*, Master's thesis, Wichita State U., 2020.

[508] MicroBooNE Collaboration, *Wire-Cell 3D Pattern Recognition Techniques for Neutrino Event Reconstruction in Large LArTPCs: Algorithm Description and Quantitative Evaluation with MicroBooNE Simulation*, *JINST* **17** (10, 2021) P01037, [2110.13961].

[509] MicroBooNE Collaboration, *Electromagnetic Shower Reconstruction and Energy Validation with Michel Electrons and π^0 Samples for the Deep-Learning-Based Analyses in MicroBooNE*, *JINST* **16** (10, 2021) T12017, [2110.11874].

[510] K. Carloni, N. W. Kamp, A. Schneider and J. M. Conrad, *Convolutional Neural Networks for Shower Energy Prediction in Liquid Argon Time Projection Chambers*, *JINST* **17** (10, 2021) P02022, [2110.10766].

[511] J. García-Méndez, N. Geißelbrecht, T. Eberl, M. Ardid and S. Ardid, *Deep learning reconstruction in ANTARES*, *JINST* **16** (7, 2021) C09018, [2107.13654].

[512] A. Gavrikov and F. Ratnikov, *The use of Boosted Decision Trees for Energy Reconstruction in JUNO experiment*, in *25th International Conference on Computing in High-Energy and Nuclear Physics*, vol. 251, p. 03014, 6, 2021. 2106.02907. DOI.

[513] D. Maksimović, M. Nieslony and M. Wurm, *CNNs for enhanced background discrimination in DSNB searches in large-scale water-Gd detectors*, *JCAP* **11** (4, 2021) 051, [2104.13426].

[514] ArgoNeuT Collaboration, *A deep-learning based raw waveform region-of-interest*

finder for the liquid argon time projection chamber, *JINST* **17** (3, 2021) P01018, [2103.06391].

[515] F. Drielsma, K. Terao, L. Dominé and D. H. Koh, *Scalable, End-to-End, Deep-Learning-Based Data Reconstruction Chain for Particle Imaging Detectors*, in *34th Conference on Neural Information Processing Systems*, 2, 2021. 2102.01033.

[516] I. Collaboration, *A Convolutional Neural Network based Cascade Reconstruction for the IceCube Neutrino Observatory*, 2021. 10.1088/1748-0221/16/07/P07041.

[517] S. Y.-C. Chen, T.-C. Wei, C. Zhang, H. Yu and S. Yoo, *Quantum Convolutional Neural Networks for High Energy Physics Data Analysis*, *Phys.Rev.Res.* **4** (12, 2020) 013231, [2012.12177]. 5

[518] MicroBooNE Collaboration, *Semantic Segmentation with a Sparse Convolutional Neural Network for Event Reconstruction in MicroBooNE*, *Phys.Rev.D* **103** (12, 2020) 052012, [2012.08513].

[519] J. Liu, J. Ott, J. Collado, B. Jargowsky, W. Wu, J. Bian et al., *Deep-Learning-Based Kinematic Reconstruction for DUNE*, 2012.06181.

[520] B. Clerbaux, P.-A. Petitjean, Y. Xu and Y. Yang, *Study of using machine learning for level 1 trigger decision in JUNO experiment*, *IEEE Trans.Nucl.Sci.* **68** (11, 2020) 2187, [2011.08847].

[521] MicroBooNE Collaboration, *A Convolutional Neural Network for Multiple Particle Identification in the MicroBooNE Liquid Argon Time Projection Chamber*, *Phys.Rev.D* **103** (10, 2020) 092003, [2010.08653].

[522] H. Yu et al., *Augmented signal processing in Liquid Argon Time Projection Chambers with a deep neural network*, *JINST* **16** (2021) P01036, [2007.12743].

[523] DeepLearnPhysics collaboration, D. H. Koh, P. Côte De Soux, L. Dominé, F. Drielsma, R. Itay, Q. Lin et al., *Scalable, Proposal-free Instance Segmentation Network for 3D Pixel Clustering and Particle Trajectory Reconstruction in Liquid Argon Time Projection Chambers*, 2007.03083.

[524] DeepLearnPhysics collaboration, F. Drielsma, Q. Lin, P. C. de Soux, L. Dominé, R. Itay, D. H. Koh et al., *Clustering of electromagnetic showers and particle interactions with graph neural networks in liquid argon time projection chambers*, *Phys. Rev. D* **104** (2021) 072004, [2007.01335].

[525] DUNE Collaboration, *Neutrino interaction classification with a convolutional neural network in the DUNE far detector*, *Phys. Rev. D* **102** (2020) 092003, [2006.15052].

[526] L. Dominé and K. Terao, *Point Proposal Network for Reconstructing 3D Particle Positions with Sub-Pixel Precision in Liquid Argon Time Projection Chambers*, *Phys.Rev.D* **104** (6, 2020) 032004, [2006.14745].

[527] C. Adams, K. Terao and T. Wongjirad, *PILArNet: Public Dataset for Particle Imaging Liquid Argon Detectors in High Energy Physics*, 2006.01993.

[528] KM3NeT Collaboration, *Event reconstruction for KM3NeT/ORCA using convolutional neural networks*, 2004.08254.

[529] DeepLearnPhysics collaboration, L. Dominé and K. Terao, *Scalable deep convolutional neural networks for sparse, locally dense liquid argon time projection chamber data*, *Phys. Rev. D* **102** (2020) 012005, [1903.05663].

[530] MicroBooNE Collaboration, *Deep neural network for pixel-level electromagnetic particle identification in the MicroBooNE liquid argon time projection chamber*, *Phys. Rev.* **D99** (2019) 092001, [1808.07269].

[531] L. Hertel, L. Li, P. Baldi and J. Bian, *Convolutional Neural Networks for Electron Neutrino and Electron Shower Energy Reconstruction in the NOνA Detectors*, 2017.

[532] MicroBooNE Collaboration, *Convolutional Neural Networks Applied to Neutrino Events in a Liquid Argon Time Projection Chamber*, *JINST* **12** (2017) P03011, [1611.05531].

[533] A. Aurisano, A. Radovic, D. Rocco, A. Himmel, M. D. Messier, E. Niner et al., *A Convolutional Neural Network Neutrino Event Classifier*, *JINST* **11** (2016) P09001, [1604.01444]. 4

[534] F. D. Amaro et al., *Bayesian network 3D event reconstruction in the Cygno optical TPC for dark matter direct detection*, 2506.04973. 4

[535] D. Cerdeno, M. de los Rios and A. D. Perez, *Bayesian technique to combine independently-trained Machine-Learning models applied to direct dark matter detection*, *JCAP* **01** (7, 2024) 038, [2407.21008].

[536] M. Ghrear, P. Sadowski and S. E. Vahsen, *Deep Probabilistic Direction Prediction in 3D with Applications to Directional Dark Matter Detectors*, *Mach.Learn.Sci.Tech.* **5** (3, 2024) 035009, [2403.15949].

[537] XENON Collaboration, *Detector signal characterization with a Bayesian network in XENONnT*, *Phys. Rev. D* **108** (2023) 012016, [2304.05428].

[538] Z.-Y. Li, Z. Qian, J.-H. He, W. He, C.-X. Wu, X.-Y. Cai et al., *Improving the machine learning based vertex reconstruction for large liquid scintillator detectors with multiple types of PMTs*, *Nucl.Sci.Tech.* **33** (5, 2022) 93, [2205.04039].

[539] S. Liang, A. Higuera, C. Peters, V. Roy, W. U. Bajwa, H. Shatkay et al., *Domain-informed neural networks for interaction localization within astroparticle experiments*, *Front.Artif.Intell.* **5** (12, 2021) 832909, [2112.07995].

[540] J. Herrero-Garcia, R. Patrick and A. Scaffidi, *Signal-agnostic dark matter searches*

in direct detection data with machine learning, *JCAP* **02** (10, 2021) 039, [2110.12248]. 9

[541] I. Coarasa et al., *Machine-learning techniques applied to three-year exposure of ANAIS-112*, in *17th International Conference on Topics in Astroparticle and Underground Physics*, vol. 2156, p. 012036, 10, 2021. 2110.10649. DOI.

[542] J. I. McDonald, *Scanning the landscape of axion dark matter detectors: applying gradient descent to experimental design*, *Phys.Rev.D* **105** (8, 2021) 083010, [2108.13894].

[543] A. Golovatiuk, A. Ustyuzhanin, A. Alexandrov and G. De Lellis, *Deep Learning for direct Dark Matter search with nuclear emulsions*, *Comput.Phys.Commun.* **275** (6, 2021) 108312, [2106.11995].

[544] C. K. Khosa, L. Mars, J. Richards and V. Sanz, *Convolutional Neural Networks for Direct Detection of Dark Matter*, *J. Phys. G* **47** (2020) 095201, [1911.09210].

[545] LUX Collaboration, *Improving sensitivity to low-mass dark matter in LUX using a novel electrode background mitigation technique*, *Phys.Rev.D* **104** (11, 2020) 012011, [2011.09602].

[546] A. Ilyasov and A. Grobov, *Boosted decision trees approach to neck alpha events discrimination in DEAP-3600 experiment*, *Physica Scripta* (2020) . 4

[547] C. Heneka, F. Nieser, A. Ore, T. Plehn and D. Schiller, *Large Language Models – the Future of Fundamental Physics?*, 2506.14757. 4, 9

[548] M. Erdmann, N. Langner, J. Schulte and D. Wirtz, *What exactly did the Transformer learn from our physics data?*, 2505.21042. 10

[549] S. Takahashi, A. Harada and S. Yamada, *An Extended Closure Relation by LightGBM for Neutrino Radiation Transport in Core-collapse Supernovae*, *Astrophys.J.* **986** (9, 2024) 67, [2409.02719].

[550] J. Heisig, M. Korsmeier, M. Krämer, K. Nippel and L. Rathmann, *$\overline{D}$arkRayNet: Emulation of cosmic-ray antideuteron fluxes from dark matter*, *JCAP* **11** (6, 2024) 017, [2406.18642].

[551] B. Ahn, H.-S. Jeong, K.-Y. Kim and K. Yun, *Holographic reconstruction of black hole spacetime: machine learning and entanglement entropy*, *JHEP* **01** (6, 2024) 025, [2406.07395].

[552] A. Hatefi, E. Hatefi and R. J. Lopez-Sastre, *Neural Networks Assisted Metropolis-Hastings for Bayesian Estimation of Critical Exponent on Elliptic Black Hole Solution in 4D Using Quantum Perturbation Theory*, *JCAP* **09** (6, 2024) 015, [2406.04310].

[553] J.-H. Yoon, S. Cléry, M. Gross and Y. Mambrini, *Preheating with deep learning*, *JCAP* **08** (5, 2024) 031, [2405.08901].

[554] F. Riehn, A. Fedynitch and R. Engel, *Sibyll* , *Astropart. Phys.* **160** (2024) 102964, [2404.02636].

[555] P. Kalaczyński, *The Measurement and Modelling of Cosmic Ray Muons at KM3NeT Detectors*, other thesis, 2, 2024.

[556] P. Thakur, T. Malik and T. K. Jha, *Towards Uncovering Dark Matter Effects on Neutron Star Properties: A Machine Learning Approach*, *Particles* **7** (2024) 80–95, [2401.07773].

[557] L.-J. Guo, J.-Y. Xiong, Y. Ma and Y.-L. Ma, *Insights into neutron star equation of state by machine learning*, *Astrophys.J.* **965** (9, 2023) 47, [2309.11227].

[558] A. Hatefi and E. Hatefi, *Sequential Monte Carlo with Cross-validated Neural Networks for Complexity of Hyperbolic Black Hole Solutions in 4D*, *Eur.Phys.J.C* **83** (8, 2023) 1083, [2308.07907].

[559] P. G. Krastev, *A Deep Learning Approach to Extracting Nuclear Matter Properties from Neutron Star Observations*, *Symmetry* **15** (2023) 1123, [2303.17146].

[560] B.-J. Cai, B.-A. Li and Z. Zhang, *Core States of Neutron Stars from Anatomizing Their Scaled Structure Equations*, *Astrophys. J.* **952** (2023) 147, [2306.08202].

[561] V. Carvalho, M. Ferreira, T. Malik and C. Providência, *Decoding Neutron Star Observations: Revealing Composition through Bayesian Neural Networks*, *Phys.Rev.D* **108** (6, 2023) 043031, [2306.06929].

[562] W. Zhou, J. Hu, Y. Zhang and H. Shen, *Nonparametric Model for the Equations of State of a Neutron Star from Deep Neural Network*, *Astrophys. J.* **950** (2023) 186, [2305.03323].

[563] T. Kim, J. H. Kim, S. Kumar, A. Martin, M. Münchmeyer and Y. Tsai, *Probing Cosmological Particle Production and Pairwise Hotspots with Deep Neural Networks*, *Phys.Rev.D* **108** (3, 2023) 043525, [2303.08869].

[564] S. Goriely, A. Choplin, W. Ryssens and I. Kullmann, *Progress in Nuclear Astrophysics: a multi-disciplinary field with still many open questions*, in *28th International Nuclear Physics Conference*, vol. 2586, p. 012104, 12, 2022. 2212.02156. DOI. 4

[565] T. Nguyen, S. Mishra-Sharma, R. Williams and L. Necib, *Uncovering dark matter density profiles in dwarf galaxies with graph neural networks*, *Phys.Rev.D* **107** (8, 2022) 043015, [2208.12825].

[566] G. Zhang, S. Mishra-Sharma and C. Dvorkin, *Inferring subhalo effective density*

slopes from strong lensing observations with neural likelihood-ratio estimation, 2208.13796.

[567] S. Abel, A. Constantin, T. R. Harvey and A. Lukas, *Cosmic Inflation and Genetic Algorithms*, *Fortsch.Phys.* **71** (8, 2022) 2200161, [2208.13804].

[568] Y. Sun and T. R. Slatyer, *Modeling early-universe energy injection with Dense Neural Networks*, *Phys.Rev.D* **107** (7, 2022) 063541, [2207.06425].

[569] T. Glauch, T. Kerscher and P. Giommi, *BlaST – A Machine-Learning Estimator for the Synchrotron Peak of Blazars*, *Astron.Comput.* **41** (7, 2022) 100646, [2207.03813].

[570] N. A. Montel, A. Coogan, C. Correa, K. Karchev and C. Weniger, *Estimating the warm dark matter mass from strong lensing images with truncated marginal neural ratio estimation*, *Mon.Not.Roy.Astron.Soc.* **518** (5, 2022) 2746, [2205.09126].

[571] S. De, W. Maitra, V. Rentala and A. M. Thalapillil, *Deep learning techniques for Imaging Air Cherenkov Telescopes*, *Phys.Rev.D* **107** (6, 2022) 083026, [2206.05296].

[572] Y. Chen and B.-Q. Ma, *Novel pre-burst stage of gamma-ray bursts from machine learning*, *JHEAp* **32** (2021) 128, [1910.08043].

[573] T. Bister, M. Erdmann, U. Köthe and J. Schulte, *Inference of cosmic-ray source properties by conditional invertible neural networks*, *Eur.Phys.J.C* **82** (10, 2021) 171, [2110.09493]. 8

[574] S. Mishra-Sharma and K. Cranmer, *A neural simulation-based inference approach for characterizing the Galactic Center γ-ray excess*, *Phys.Rev.D* **105** (10, 2021) 063017, [2110.06931]. 10

[575] S. Mishra-Sharma, *Inferring dark matter substructure with astrometric lensing beyond the power spectrum*, in *35th Conference on Neural Information Processing Systems*, vol. 3, p. 01LT03, 10, 2021. 2110.01620. DOI.

[576] C. G. Sabiu, K. Kadota, J. Asorey and I. Park, *Probing Ultra-light Axion Dark Matter from 21cm Tomography using Convolutional Neural Networks*, *JCAP* **01** (8, 2021) 020, [2108.07972].

[577] F. Kahlhoefer, M. Korsmeier, M. Krämer, S. Manconi and K. Nippel, *Constraining dark matter annihilation with cosmic ray antiprotons using neural networks*, *JCAP* **12** (7, 2021) 037, [2107.12395].

[578] F. List, N. L. Rodd and G. F. Lewis, *Dim but not entirely dark: Extracting the Galactic Center Excess' source-count distribution with neural nets*, *Phys.Rev.D* **104** (7, 2021) 123022, [2107.09070].

[579] N. O. P. Vago, I. A. Hameed and M. Kachelriess, *Using Convolutional Neural*

Networks for the Helicity Classification of Magnetic Fields, in *37th International Cosmic Ray Conference*, vol. ICRC2021, p. 906, 6, 2021. 2106.06718. DOI.

[580] A. Aizpuru, R. Arjona and S. Nesseris, *Machine Learning improved fits of the sound horizon at the baryon drag epoch*, *Phys.Rev.D* **104** (6, 2021) 043521, [2106.00428].

[581] T. Ikeda, T. Tanimori, A. Takada, Y. Mizumura, K. Yoshikawa, M. Abe et al., *Development of Convolutional Neural Networks for an Electron-Tracking Compton Camera*, *PTEP* **2021** (5, 2021) 083F01, [2105.02512].

[582] D. Shih, M. R. Buckley, L. Necib and J. Tamanas, *Via Machinae: Searching for Stellar Streams using Unsupervised Machine Learning*, *Mon.Not.Roy.Astron.Soc.* **509** (4, 2021) 5992, [2104.12789]. 9

[583] A. Dropulic, B. Ostdiek, L. J. Chang, H. Liu, T. Cohen and M. Lisanti, *Machine Learning the 6th Dimension: Stellar Radial Velocities from 5D Phase-Space Correlations*, *Astrophys.J.Lett.* **915** (3, 2021) L14, [2103.14039].

[584] R. Arjona and S. Nesseris, *Novel null tests for the spatial curvature and homogeneity of the Universe and their machine learning reconstructions*, *Phys.Rev.D* **103** (3, 2021) 103539, [2103.06789].

[585] M.-Z. Han, J.-L. Jiang, S.-P. Tang and Y.-Z. Fan, *Bayesian nonparametric inference of neutron star equation of state via neural network*, *Astrophys.J.* **919** (3, 2021) 11, [2103.05408].

[586] D. Droz, A. Tykhonov, X. Wu, F. Alemanno, G. Ambrosi, E. Catanzani et al., *A neural network classifier for electron identification on the DAMPE experiment*, *JINST* **16** (2, 2021) P07036, [2102.05534].

[587] W.-C. Huang, J.-L. Kuo and Y.-L. S. Tsai, *A convolutional-neural-network estimator of CMB constraints on dark matter energy injection*, 2021. 10.1088/1475-7516/2021/06/025.

[588] R. Conceição, B. S. González, A. Guillén, M. Pimenta and B. Tomé, *Muon identification in a compact single-layered water Cherenkov detector and gamma/hadron discrimination using Machine Learning techniques*, *Eur.Phys.J.C* **81** (1, 2021) 542, [2101.10109].

[589] B. S. González, R. C. ao, M. Pimenta, B. Tomé and A. Guillén, *Tackling the muon identification in water Cherenkov detectors problem for the future Southern Wide-field Gamma-ray Observatory by means of Machine Learning*, 2021.

[590] DarkMachines High Dimensional Sampling Group collaboration, C. Balázs et al., *A comparison of optimisation algorithms for high-dimensional particle and astrophysics applications*, *JHEP* **05** (1, 2021) 108, [2101.04525]. 6

[591] Pierre Auger Collaboration, *Deep-Learning based Reconstruction of the Shower*

Maximum $X_{\max}$ using the Water-Cherenkov Detectors of the Pierre Auger Observatory, *JINST* **16** (1, 2021) P07019, [2101.02946].

[592] Y.-L. S. Tsai, Y.-L. Chung, Q. Yuan and K. Cheung, *Inverting cosmic ray propagation by Convolutional Neural Networks*, *JCAP* **03** (11, 2020) 044, [2011.11930].

[593] J. Brehmer, S. Mishra-Sharma, J. Hermans, G. Louppe and K. Cranmer, *Mining for Dark Matter Substructure: Inferring subhalo population properties from strong lenses with machine learning*, 1909.02005.

[594] B. Ostdiek, A. Diaz Rivero and C. Dvorkin, *Detecting Subhalos in Strong Gravitational Lens Images with Image Segmentation*, *Astron.Astrophys.* **657** (9, 2020) L14, [2009.06663]. 4

[595] R. Miller, A. Shmakov, K. Oh, J. Lee, P. Baldi, L. Condren et al., *Fast and Precise Track Fitting with Machine Learning*, 2505.02937. 4, 7

[596] MODE Collaboration, *Unsupervised Particle Tracking with Neuromorphic Computing*, 2502.06771. 5

[597] S. Caron, N. Dobreva, A. F. Sánchez, J. D. Martín-Guerrero, U. Odyurt, R. R. Ruiz de Austri Bazan et al., *TrackFormers: In Search of Transformer-Based Particle Tracking for the High-Luminosity LHC Era*, *Eur.Phys.J.C* **85** (7, 2024) 460, [2407.07179].

[598] J. Guiang et al., *Improving tracking algorithms with machine learning: a case for line-segment tracking at the High Luminosity LHC*, in *Connecting The Dots 2023*, 3, 2024. 2403.13166.

[599] G. Gavalian, *Real-Time Charged Track Reconstruction for CLAS12*, *JINST* **19** (3, 2024) C05050, [2403.04020].

[600] A. Huang, Y. Melkani, P. Calafiura, A. Lazar, D. T. Murnane, M.-T. Pham et al., *A Language Model for Particle Tracking*, in *Connecting The Dots 2023*, 2, 2024. 2402.10239.

[601] C. Allaire, F. Bouvet, H. Grasland and D. Rousseau, *Ranking-based neural network for ambiguity resolution in ACTS*, in *26th International Conference on Computing in High Energy & Nuclear Physics*, vol. 295, p. 03022, 12, 2023. 2312.05070. DOI.

[602] C. Allaire, R. B. Garg, H. B. Grasland, E. F. Hofgard, D. Rousseau, R. Salahat et al., *Auto-tuning capabilities of the ACTS track reconstruction suite*, in *21th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI meets Reality*, 12, 2023. 2312.05123. 4

[603] M. Mieskolainen, *HyperTrack: Neural Combinatorics for High Energy Physics*, in

26th International Conference on Computing in High Energy & Nuclear Physics, vol. 295, p. 09021, 9, 2023. 2309.14113. DOI.

[604] S. Akar, M. Peters, H. Schreiner, M. D. Sokoloff and W. Tepe, *Comparing and improving hybrid deep learning algorithms for identifying and locating primary vertices*, in *21th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI meets Reality*, 4, 2023. 2304.02423.

[605] M. Knipfer, S. Meier, J. Heimerl, P. Hommelhoff and S. Gleyzer, *Deep Learning-Based Spatiotemporal Multi-Event Reconstruction for Delay Line Detectors*, *Mach.Learn.Sci.Tech.* **5** (6, 2023) 025019, [2306.09359].

[606] J. W. Bae, T. C. Wu and I. Jovanovic, *Reconstruction of fast neutron direction in segmented organic detectors using deep learning*, *Nucl. Instrum. Meth. A* **1049** (2023) 168024, [2301.10796].

[607] H. Abidi, A. Boveia, V. Cavaliere, D. Furletov, A. Gekow, C. W. Kalderon et al., *Charged Particle Tracking with Machine Learning on FPGAs*, 2212.02348. 6

[608] C. Sun, T. Nakajima, Y. Mitsumori, Y. Horii and M. Tomoto, *Fast muon tracking with machine learning implemented in FPGA*, *Nucl. Instrum. Meth. A* **1045** (2023) 167546, [2202.04976]. 6

[609] A. Akram and X. Ju, *Track Reconstruction using Geometric Deep Learning in the Straw Tube Tracker (STT) at the PANDA Experiment*, 8, 2022. 2208.12178.

[610] O. Bakina et al., *Deep learning for track recognition in pixel and strip-based particle detectors*, *JINST* **17** (10, 2022) P12023, [2210.00599].

[611] S. Alonso-Monsalve, D. Sgalaberna, X. Zhao, C. McGrew and A. Rubbia, *Artificial intelligence for improved fitting of trajectories of elementary particles in inhomogeneous dense materials immersed in a magnetic field*, *Commun.Phys.* **6** (11, 2022) 119, [2211.04890].

[612] C.-Y. Wang et al., *Reconstruction of Large Radius Tracks with the Exa.TrkX pipeline*, in *20th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI Decoded - Towards Sustainable, Diverse, Performant and Effective Scientific Computing*, vol. 2438, p. 012117, 3, 2022. 2203.08800. DOI.

[613] P. Goncharov, E. Schavelev, A. Nikolskaya and G. Ososkov, *Ariadne: PyTorch Library for Particle Track Reconstruction Using Deep Learning*, in *24th International Scientific Conference of Young Scientists and Specialists*, vol. 2377, p. 040004, 9, 2021. 2109.08982. DOI. 6

[614] B. Huth, A. Salzburger and T. Wettig, *Machine learning for surface prediction in*

ACTS, in *25th International Conference on Computing in High-Energy and Nuclear Physics*, vol. 251, p. 03053, 8, 2021. 2108.03068. DOI.

[615] E. Lavrik, M. Shiroya, H. R. Schmidt, A. Toia and J. M. Heuser, *Optical Inspection of the Silicon Micro-strip Sensors for the CBM Experiment employing Artificial Intelligence*, *Nucl.Instrum.Meth.A* **1021** (7, 2021) 165932, [2107.07714].

[616] A. Edmonds, D. Brown, L. Vinas and S. Pagan, *Using Machine Learning to Select High-Quality Measurements*, *JINST* **16** (5, 2021) T08010, [2106.08891].

[617] X. Ju et al., *Physics and Computing Performance of the Exa.TrkX TrackML Pipeline*, *Eur.Phys.J.C* **81** (3, 2021) 876, [2103.06995].

[618] S. Akar, G. Atluri, T. Boettcher, M. Peters, H. Schreiner, M. Sokoloff et al., *Progress in developing a hybrid deep learning algorithm for identifying and locating primary vertices*, *EPJ Web Conf.* **251** (3, 2021) 04012, [2103.04962].

[619] S. Amrouche, M. Kiehn, T. Golling and A. Salzburger, *Hashing and metric learning for charged particle tracking*, *33rd Annual Conference on Neural Information Processing Systems* (1, 2021) , [2101.06428].

[620] P. J. Fox, S. Huang, J. Isaacson, X. Ju and B. Nachman, *Beyond 4D Tracking: Using Cluster Shapes for Track Seeding*, *JINST* **16** (12, 2020) P05001, [2012.04533].

[621] F. Siviero, R. Arcidiacono, N. Cartiglia, M. Costa, M. Ferrero, M. Mandurrino et al., *First application of machine learning algorithms to the position reconstruction in Resistive Silicon Detectors*, 2011.02410.

[622] S. Akar, T. J. Boettcher, S. Carl, H. F. Schreiner, M. D. Sokoloff, M. Stahl et al., *An updated hybrid deep learning algorithm for identifying and locating primary vertices*, 2007.01023.

[623] S. Amrouche et al., *The Tracking Machine Learning challenge : Accuracy phase*, 1904.06778.

[624] S. Farrell et al., *Novel deep learning methods for track reconstruction*, *4th International Workshop Connecting The Dots 2018* (10, 2018) , [1810.06111].

[625] S. Farrell, P. Calafiura, M. Mudigonda, Prabhat, D. Anderson, J. Bendavid et al., *Particle Track Reconstruction with Deep Learning*, 2017. 4

[626] M. A. Halabi et al., *Machine Learning Power Week 2023: Clustering in Hadronic Calorimeters*, 2508.09938. 4, 6

[627] S. A. Sundberg and R. J. Furnstahl, *Criticality analysis of nuclear binding energy neural networks*, 2508.01001. 11

[628] D. Stewart and J. Putschke, *Fast prediction of the hydrodynamic QGP evolution in ultra-relativistic heavy-ion collisions using Fourier Neural Operators*, 2507.23598. 7

[629] J. Mei, L. Wang and M. Huang, *Neural network extraction of chromo-electric and chromo-magnetic gluon masses*, 2507.22012.

[630] S. Guo, L. Wang, K. Zhou and G.-L. Ma, *Neural Unfolding of the Chiral Magnetic Effect in Heavy-Ion Collisions*, 2507.05808. 10

[631] W.-L. Wu, L. Meng and S.-L. Zhu, *DeepQuark: deep-neural-network approach to multiquark bound states*, 2506.20555.

[632] S. Barrera Cabodevila, A. Kurkela and F. Lindenbauer, *Solving the QCD effective kinetic theory with neural networks*, 2506.19632.

[633] T. Jenegger, N. Hartman, R. Gernhaeuser, L. Heinrich and L. Fabbietti, *Machine Learning for the Cluster Reconstruction in the CALIFA Calorimeter at R3B*, 2506.09088.

[634] V. A. A. Chavez and D. L. B. Sombillo, *Line shape analysis of* $\Lambda(1405)$ *in* $\gamma p \to K^+\Sigma^-\pi^+$ *reaction using convolutional neural network*, in *21st International Conference on Hadron Spectroscopy and Structure*, 6, 2025. 2506.04622.

[635] J. Giroux and C. Fanelli, *Towards Foundation Models for Experimental Readout Systems Combining Discrete and Continuous Data*, 2505.08736. 9

[636] H. Hou and B. Liu, *Goodness-of-fit for amplitude analysis with anomaly detection*, 2504.17494. 9

[637] Y. Hirono, K. Ikeda, D. E. Kharzeev, Z. Liu and S. Shi, *Optimal Observables for the Chiral Magnetic Effect from Machine Learning*, 2504.03248. 10

[638] Y.-J. Huang, Z. Meng, L.-G. Pang and X.-N. Wang, *A Novel Deep Learning Method for Detecting Nucleon-Nucleon Correlations*, 2504.00790.

[639] W.-C. Dai, O.-Y. Luo, B. Chen, X. Chen, X.-Y. Zhu and X.-H. Li, *Extracting Transport Properties of Quark-Gluon Plasma from the Heavy-Quark Potential With Neural Networks in a Holographic Model*, 2503.10213. 9

[640] M. Omana Kuttan, K. Zhou, J. Steinheimer and H. Stöcker, *Ultra fast, event-by-event heavy-ion simulations for next generation experiments*, 2502.16330. 8

[641] J. a. A. Gonçalves and J. G. Milhano, *Apples to Apples in Jet Quenching: robustness of Machine Learning classification of quenched jets to Underlying Event contamination*, 2501.14015.

[642] D. Stewart and J. Putschke, *Neural network biased corrections: Cautionary study in background corrections for quenched jets*, *Phys.Rev.C* **111** (12, 2024) 054902, [2412.15440].

[643] R. Li, Y.-L. Du and S. Cao, *Jet momentum reconstruction in the QGP background with machine learning*, 2412.06466.

[644] A. Ferreira et al., *AI Meets Antimatter: Unveiling Antihydrogen Annihilations*, in *38th conference on Neural Information Processing Systems*, 12, 2024. 2412.00961.

[645] U. S. Qureshi and R. Kunnawalkam Elayavalli, *Model-Agnostic Tagging of Quenched Jets in Heavy-Ion Collisions*, 2411.19389.

[646] K. M. Graczyk, B. E. Kowal, A. M. Ankowski, R. D. Banerjee, J. L. Bonilla, H. Prasad et al., *Electron-nucleus cross sections from transfer learning*, *Phys.Rev.Lett.* **135** (8, 2024) 5, [2408.09936].

[647] JETSCAPE Collaboration, *Bayesian Inference analysis of jet quenching using inclusive jet and hadron suppression measurements*, *Phys.Rev.C* **111** (8, 2024) 054913, [2408.08247]. 10

[648] S. Liuti et al., *AI for Nuclear Physics: the EXCLAIM project*, *JINST* **20** (7, 2024) C08011, [2408.00163].

[649] H. Hirvonen, M. Kuha, J. Auvinen, K. J. Eskola, Y. Kanakubo and H. Niemi, *Effects of saturation and fluctuating hotspots for flow observables in ultrarelativistic heavy-ion collisions*, *Phys.Rev.C* **110** (7, 2024) 034911, [2407.01338].

[650] L. M. Santos, V. A. A. Chavez and D. L. B. Sombillo, *Pole structure of $P_\psi^N(4312)^+$ via machine learning and uniformized S-matrix*, *J.Phys.G* **52** (5, 2024) 015104, [2405.11906].

[651] K. Goswami, S. Prasad, N. Mallick, R. Sahoo and G. B. Mohanty, *A machine learning-based study of open-charm hadrons in proton-proton collisions at the Large Hadron Collider*, *Phys.Rev.D* **110** (4, 2024) 034017, [2404.09839].

[652] H. Hirvonen, K. J. Eskola and H. Niemi, *Deep learning for flow observables in high energy heavy-ion collisions*, in *30th International Conference on Ultrarelativstic Nucleus-Nucleus Collisions*, vol. 296, p. 02002, 4, 2024. 2404.02602. DOI.

[653] T. Mengel, P. Steffanic, C. Hughes, A. C. O. Da Silva and C. Nattrass, *Multiplicity Based Background Subtraction for Jets in Heavy Ion Collisions*, 2402.10945.

[654] Z. Wang et al., *Physics-informed Meta-instrument for eXperiments (PiMiX) with applications to fusion energy*, 1, 2024. 2401.08390.

[655] D. Lay, E. Flynn, S. A. Giuliani, W. Nazarewicz and L. Neufcourt, *Neural Network Emulation of Spontaneous Fission*, *Phys.Rev.C* **109** (10, 2023) 044305, [2310.01608].

[656] P. F. Bedaque, H. Kumar and A. Sheng, *Neural Network Solutions of Bosonic Quantum Systems in One Dimension*, *Phys.Rev.C* **109** (9, 2023) 034004, [2309.02352].

[657] P. Wen, J. W. Holt and M. Li, *Generative modeling of nucleon-nucleon interactions*, *Phys.Rev.Lett.* **133** (6, 2023) 252501, [2306.13007]. 8

[658] N. Hizawa, K. Hagino and K. Yoshida, *Analysis of a Skyrme energy density functional with deep learning*, *Phys.Rev.C* **108** (6, 2023) 034311, [2306.11314].

[659] S. Liu, Z. Gao, Z. Liao, Y. Yang, J. Su, Y. Wang et al., *Constraining the Woods-Saxon potential in fusion reactions based on a physics-informed neural network*, *Phys.Rev.C* **109** (6, 2023) 024601, [2306.11236].

[660] S. Yoshida, *IMSRG-Net: A machine learning-based solver for In-Medium Similarity Renormalization Group*, *Phys.Rev.C* **108** (6, 2023) 044303, [2306.08878].

[661] R.-D. Lasseri, D. Regnier, M. Frosini, M. Verriere and N. Schunck, *Generative deep-learning reveals collective variables of Fermionic systems*, *Phys.Rev.C* **109** (6, 2023) 064612, [2306.08348]. 8

[662] A. Karmakar, A. Pal, G. A. Kumar, Bhavika, V. Anand and M. Tyagi, *Neutron-Gamma Pulse Shape Discrimination for Organic Scintillation Detector using 2D CNN based Image Classification*, *Appl.Radiat.Isot.* **217** (6, 2023) 111653, [2306.09356].

[663] T. C. Yiu, H. Liang and J. Lee, *Nuclear mass predictions based on deep neural network and finite-range droplet model (2012)*, *Chin.Phys.C* **48** (6, 2023) 024102, [2306.04171].

[664] P. Ai, L. Xiao, Z. Deng, Y. Wang, X. Sun, G. Huang et al., *Label-free timing analysis of modularized nuclear detectors with physics-constrained deep learning*, *Mach.Learn.Sci.Tech.* **4** (4, 2023) 045020, [2304.11930].

[665] Y. Wang and Q. Li, *Machine learning transforms the inference of the nuclear equation of state*, *Front. Phys. (Beijing)* **18** (2023) 64402, [2305.16686].

[666] H.-S. Wang, S. Guo, K. Zhou and G.-L. Ma, *A machine learning study to identify collective flow in small and large colliding systems*, *Phys.Rev.C* **110** (5, 2023) 2, [2305.09937].

[667] O. Al Hammal, M. Martini, J. Frontera-Pons, T. H. Nguyen and R. Pérez-Ramos, *Neural network predictions of inclusive electron-nucleus cross sections*, *Phys. Rev. C* **107** (2023) 065501, [2305.08217]. 7

[668] B. Dellen, U. Jaekel, P. S. A. Freitas and J. W. Clark, *Predicting nuclear masses with product-unit networks*, *Phys.Lett.B* **852** (5, 2023) 138608, [2305.04675].

[669] S. Lin et al., *Demonstration of Sub-micron UCN Position Resolution using Room-temperature CMOS Sensor*, *Nucl.Instrum.Meth.A* **1057** (5, 2023) 168769, [2305.09562].

[670] M. Soleymaninia, H. Hashamipour, H. Khanpour, S. Shoeib and A. Mohamaditabar, *Nuclear corrections on the charged hadron fragmentation functions in a Neural Network global QCD analysis*, *Eur.Phys.J.Plus* **139** (5, 2023) 794, [2305.02664]. 6

[671] J. Shi, L.-C. Gui, J. Liang and G. Liu, Σ *Resonances from a Neural Network-based Partial Wave Analysis on K^-p Scattering*, 2305.01852. 7

[672] D. Basak and K. Dey, *Estimation of collision centrality in terms of the number of participating nucleons in heavy-ion collisions using deep learning*, *Eur.Phys.J.A* **59** (4, 2023) 174, [2305.00493]. 6

[673] W.-B. He, Y.-G. Ma, L.-G. Pang, H. Song and K. Zhou, *High energy nuclear physics meets Machine Learning*, *Nucl.Sci.Tech.* **34** (3, 2023) 88, [2303.06752].

[674] G. Bíró and G. G. Barnaföldi, *Machine Learning based KNO-scaling of charged hadron multiplicities with Hijing++*, in *21th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI meets Reality*, 3, 2023. 2303.05422.

[675] H. Hirvonen, K. J. Eskola and H. Niemi, *Deep learning for flow observables in ultrarelativistic heavy-ion collisions*, *Phys.Rev.C* **108** (3, 2023) 034905, [2303.04517].

[676] J. Escher et al., *Improving nuclear data evaluations with predictive reaction theory and indirect measurements*, in *15th International Conference on Nuclear Data for Science and Technology*, 4, 2023. 2304.10034. DOI.

[677] M. Mumpower, M. Li, T. M. Sprouse, B. S. Meyer, A. E. Lovell and A. T. Mohan, *Bayesian averaging for ground state masses of atomic nuclei in a Machine Learning approach*, *Front. in Phys.* **11** (2023) 1198572, [2304.08546].

[678] G. Kanwar, A. Lovato, N. Rocco and M. Wagman, *Mitigating Green's function Monte Carlo signal-to-noise problems using contour deformations*, *Phys.Rev.C* **109** (4, 2023) 034317, [2304.03229].

[679] J. Xu, *Bayesian inference of nucleus resonance and neutron skin*, *Atomic Energ. Sci. Technol.* **57** (2023) 721, [2301.07884].

[680] W. He, Q. Li, Y. Ma, Z. Niu, J. Pei and Y. Zhang, *Machine learning in nuclear physics at low and intermediate energies*, *Sci. China Phys. Mech. Astron.* **66** (2023) 282001, [2301.06396].

[681] N. Mallick, S. Prasad, A. N. Mishra, R. Sahoo and G. G. Barnaföldi, *Deep learning predicted elliptic flow of identified particles in heavy-ion collisions at the RHIC and LHC energies*, *Phys.Rev.D* **107** (1, 2023) 094001, [2301.10426].

[682] P. Steffanic, C. Hughes and C. Nattrass, *Separating signal from combinatorial jets in a high background environment*, *Phys.Rev.C* **108** (1, 2023) 024909, [2301.09148].

[683] B. Fore, J. M. Kim, G. Carleo, M. Hjorth-Jensen, A. Lovato and M. Piarulli, *Dilute neutron star matter from neural-network quantum states*, *Phys. Rev. Res.* **5** (2023) 033062, [2212.04436].

[684] N. Mallick, S. Prasad, A. N. Mishra, R. Sahoo and G. G. Barnaföldi, *Estimating elliptic flow coefficient in heavy ion collisions using deep learning*, *Phys. Rev. D* **105** (2022) 114022, [2203.01246].

[685] J. M. Munoz, S. Akkoyun, Z. P. Reyes and L. A. Pachon, *Predicting β-decay energy with machine learning*, *Phys. Rev. C* **107** (2023) 034308, [2211.17136].

[686] Y. Yang and P. Zhao, *Deep-neural-network approach to solving the ab initio nuclear structure problem*, *Phys. Rev. C* **107** (2023) 034320, [2211.13998].

[687] M. Rigo, B. Hall, M. Hjorth-Jensen, A. Lovato and F. Pederiva, *Solving the nuclear pairing model with neural network quantum states*, *Phys. Rev. E* **107** (2023) 025310, [2211.04614].

[688] Z.-X. Yang, X.-H. Fan, Z.-P. Li and H. Liang, *A Kohn-Sham scheme based neural network for nuclear systems*, *Phys. Lett. B* **840** (2023) 137870, [2212.02093].

[689] X. Zhang, W. Lin, J. M. Yao, C. F. Jiao, A. M. Romero, T. R. Rodríguez et al., *Optimization of the generator coordinate method with machine-learning techniques for nuclear spectra and neutrinoless double-β decay: Ridge regression for nuclei with axial deformation*, *Phys. Rev. C* **107** (2023) 024304, [2211.02797].

[690] G. Bíró, B. Tankó-Bartalis and G. G. Barnaföldi, *Testing of KNO-scaling of charged hadron multiplicities within a Machine Learning based approach*, *PoS* **ICHEP2022** (2022) 1188, [2210.10548].

[691] K. Lee, J. Mulligan, M. Ploskon, F. Ringer and F. Yuan, *Machine learning-based jet and event classification at the Electron-Ion Collider with applications to hadron structure and spin physics*, *JHEP* **03** (10, 2022) 085, [2210.06450].

[692] A. Saha, D. Dan and S. Sanyal, *Machine Learning model driven prediction of the initial geometry in Heavy-Ion Collision experiments*, *Phys.Rev.C* **106** (3, 2022) 014901, [2203.15433].

[693] H. Chen, W.-Q. Niu and H.-Q. Zheng, *Identify Hadronic Molecule States by Neural Network*, *Eur.Phys.J.C* **83** (5, 2022) 52, [2205.03572].

[694] C. Fanelli et al., *AI-assisted Optimization of the ECCE Tracking System at the Electron Ion Collider*, *Nucl.Instrum.Meth.A* **1047** (5, 2022) 167748, [2205.09185].

[695] L. Liu, M. Verweij and J. Velkovska, *Identifying quenched jets in heavy ion collisions with machine learning*, *JHEP* **04** (6, 2022) 140, [2206.01628].

[696] D. Liyanage, Y. Ji, D. Everett, M. Heffernan, U. Heinz, S. Mak et al., *Efficient emulation of relativistic heavy ion collisions with transfer learning*, *Phys.Rev.C* **105** (1, 2022) 034910, [2201.07302].

[697] M. Boglione, M. Diefenthaler, S. Dolan, L. Gamberg, W. Melnitchouk, D. Pitonyak

et al., *New tool for kinematic regime estimation in semi-inclusive deep-inelastic scattering*, *JHEP* **04** (1, 2022) 084, [2201.12197].

[698] R. M. A. Rahman, M. Y. El-Bakry, D. M. Habashy, A. N. Tawfik and M. Hanafy, *Particle ratios with in Hadron Resonance Gas (HRG) and Artificial Neural Network (ANN) models*, 2201.04444.

[699] S. Soma, L. Wang, S. Shi, H. Stöcker and K. Zhou, *Neural network reconstruction of the dense matter equation of state from neutron star observables*, *JCAP* **08** (1, 2022) 071, [2201.01756].

[700] P. Xiang, Y.-S. Zhao and X.-G. Huang, *Determination of impact parameter in high-energy heavy-ion collisions via deep learning*, *Chin.Phys.C* **46** (12, 2021) 074110, [2112.03824].

[701] Y.-L. Du, D. Pablos and K. Tywoniuk, *Jet tomography in hot QCD medium with deep learning*, in *European Physical Society Conference on High Energy Physics 2021*, vol. EPS-HEP2021, p. 302, 12, 2021. 2112.00679. DOI.

[702] Y.-L. Du, D. Pablos and K. Tywoniuk, *Classification of quark and gluon jets in hot QCD medium with deep learning*, in *Particles and Nuclei International Conference* , vol. PANIC2021, p. 224, 12, 2021. 2112.00681. DOI.

[703] Y. S. Lai, J. Mulligan, M. Płoskoń and F. Ringer, *The information content of jet quenching and machine learning assisted observable design*, *JHEP* **10** (11, 2021) 011, [2111.14589].

[704] G. Bíró, B. Tankó-Bartalis and G. G. Barnaföldi, *Studying Hadronization by Machine Learning Techniques*, 2111.15655.

[705] D. M. Habashy, M. Y. El-Bakry, W. Scheinast and M. Hanafy, *Entropy per rapidity in Pb-Pb central collisions using Thermal and Artificial neural network(ANN) models at LHC energies*, *Chin.Phys.C* **46** (10, 2021) 073103, [2110.15026].

[706] JPAC collaboration, L. Ng, L. Bibrzycki, J. Nys, C. Fernandez-Ramirez, A. Pilloni, V. Mathieu et al., *Deep Learning Exotic Hadrons*, *Phys.Rev.D* **105** (10, 2021) L091501, [2110.13742].

[707] A. N. Mishra, N. Mallick, S. Tripathy, S. Deb and R. Sahoo, *Implementation of machine learning techniques to predict impact parameter and transverse spherocity in heavy-ion collisions at the LHC*, in *9th Large Hadron Collider Physics Conference*, vol. LHCP2021, p. 265, 10, 2021. 2110.04026. DOI.

[708] E. Zepeda and A. Ortiz, *Multiparton Interactions in pp collisions from Machine Learning*, in *9th Large Hadron Collider Physics Conference*, vol. LHCP2021, p. 347, 10, 2021. 2110.01748. DOI.

[709] D. M. Habashy, M. Y. El-Bakry, A. N. Tawfik, R. M. A. Rahman and M. Hanafy,

Particles Multiplicity Based on Rapidity in Landau and Artificial Neural Network(ANN) Models, *Int.J.Mod.Phys.A* **37** (9, 2021) 2250002, [2109.07191].

[710] J. He, W.-B. He, Y.-G. Ma and S. Zhang, *Machine-learning-based identification for initial clustering structure in relativistic heavy-ion collisions*, *Phys.Rev.C* **104** (9, 2021) 044902, [2109.06277].

[711] E. Shokr, A. De Roeck and M. A. Mahmoud, *Modeling of charged-particle multiplicity and transverse-momentum distributions in pp collisions using a DNN*, *Sci.Rep.* **12** (8, 2021) 8449, [2108.06102].

[712] Y.-G. Huang, L.-G. Pang, X. Luo and X.-N. Wang, *Probing criticality with deep learning in relativistic heavy-ion collisions*, *Phys.Lett.B* **827** (7, 2021) 137001, [2107.11828].

[713] M. O. Kuttan, K. Zhou, J. Steinheimer, A. Redelbach and H. Stoecker, *An equation-of-state-meter for CBM using PointNet*, *JHEP* **10** (7, 2021) 184, [2107.05590].

[714] Y.-L. Du, D. Pablos and K. Tywoniuk, *Jet tomography in heavy ion collisions with deep learning*, *Phys.Rev.Lett.* **128** (6, 2021) 012301, [2106.11271].

[715] S. Brown, G. Niculescu and I. Niculescu, *inclusiveAI: A machine learning representation of the F_2 structure function over all charted Q^2 and x range*, *Phys.Rev.C* **104** (6, 2021) 064321, [2106.06390].

[716] L. Apolinário, N. F. Castro, M. Crispim Romão, J. G. Milhano, R. Pedro and F. C. R. Peres, *Deep Learning for the Classification of Quenched Jets*, *JHEP* **11** (6, 2021) 219, [2106.08869].

[717] M. Zhou, F. Gao, J. Chao, Y.-X. Liu and H. Song, *Application of radial basis functions neutral networks in spectral functions*, *Phys.Rev.D* **104** (6, 2021) 076011, [2106.08168].

[718] D. L. B. Sombillo, Y. Ikeda, T. Sato and A. Hosaka, *Classifying near-threshold enhancement using deep neural network*, in *8th Asia-Pacific conference on Few-Body problems in Physics: Yamada Conference LXXII*, vol. 62, p. 52, 6, 2021. 2106.03453. DOI.

[719] Y.-S. Zhao, L. Wang, K. Zhou and X.-G. Huang, *Detecting Chiral Magnetic Effect via Deep Learning*, *Phys.Rev.C* **106** (5, 2021) L051901, [2105.13761].

[720] S. Nagu, J. Singh, J. Singh and R. B. Singh, *Constraining nuclear effects in Argon using machine learning algorithms*, 2105.12733.

[721] N. Mallick, S. Tripathy, A. N. Mishra, S. Deb and R. Sahoo, *Estimation of Impact Parameter and Transverse Spherocity in heavy-ion collisions at the LHC energies using Machine Learning*, *Phys. Rev. D* **103** (2021) 094031, [2103.01736].

[722] L.-G. Pang, K. Zhou, N. Su, H. Petersen, H. Stöcker and X.-N. Wang, *An equation-of-state-meter of quantum chromodynamics transition from deep learning*, *Nature Commun.* **9** (2018) 210, [1612.04262]. 4

[723] J. Bardhan, C. Neeraj, S. Mitra and T. Mandal, *Loss function to optimise signal significance in particle physics*, in *38th conference on Neural Information Processing Systems*, 12, 2024. 2412.09500. 4

[724] J. Schroff and X. Ju, *Event Generator Tuning Incorporating Systematic Uncertainty*, in *26th International Conference on Computing in High Energy & Nuclear Physics*, vol. 295, p. 06010, 10, 2023. 2310.07566. DOI.

[725] G. DeZoort and B. Hanin, *Principles for Initialization and Architecture Selection in Graph Neural Networks with ReLU Activations*, 2306.11668.

[726] A. Bevan, R. G. Go ni, T. Stevenson and T. Stevenson, *Support vector machines and generalisation in HEP*, *J. Phys. Conf. Ser.* **898** (2017) 072021, [1702.04686].

[727] L. Dudko, P. Volkov, G. Vorotnikov and A. Zaborenko, *Application of Deep Learning Technique to an Analysis of Hard Scattering Processes at Colliders*, vol. DLCP2021, p. 012, 9, 2021. 2109.08520. DOI.

[728] L. Tani, D. Rand, C. Veelken and M. Kadastik, *Evolutionary algorithms for hyperparameter optimization in machine learning for application in high energy physics*, 2011.04434. 4

[729] P. Rieck, K. Cranmer, E. Dreyer, E. Gross, N. Kakati, D. Kobylanskii et al., *Self-Supervised Learning Strategies for Jet Physics*, 2503.11632. 5

[730] Z.-E. Chen, C.-W. Chiang and F.-Y. Hsieh, *Improving the performance of weak supervision searches using data augmentation*, 2412.00198.

[731] B. Lieberman, A. Crivellin, S.-E. Dahbi, F. Stevenson, N. Tripathi, M. Kumar et al., *Trials Factor for Semi-Supervised NN Classifiers in Searches for Narrow Resonances at the LHC*, *SciPost Phys.Core* **7** (4, 2024) 073, [2404.07822].

[732] H. Beauchesne, Z.-E. Chen and C.-W. Chiang, *Improving the performance of weak supervision searches using transfer and meta-learning*, *JHEP* **02** (12, 2023) 138, [2312.06152].

[733] E. Witkowski, B. Nachman and D. Whiteson, *Learning to Isolate Muons in Data*, *Phys.Rev.D* **108** (6, 2023) 092008, [2306.15737].

[734] M. J. Dolan and A. Ore, *TopicFlow: Disentangling quark and gluon jets with normalizing flows*, *Phys.Rev.D* **107** (11, 2022) 114003, [2211.16053]. 8

[735] M. LeBlanc, B. Nachman and C. Sauer, *Going off topics to demix quark and gluon jets in α_S extractions*, *JHEP* **02** (2023) 150, [2206.10642].

[736] T. Finke, M. Krämer, M. Lipp and A. Mück, *Boosting mono-jet searches with model-agnostic machine learning*, *JHEP* **08** (2022) 015, [2204.11889]. 9

[737] T. Li, S. Liu, Y. Feng, G. Paspalaki, N. Tran, M. Liu et al., *Semi-supervised Graph Neural Networks for Pileup Noise Removal*, *Eur.Phys.J.C* **83** (3, 2022) 99, [2203.15823]. 6

[738] P. T. Komiske, S. Kryhin and J. Thaler, *Disentangling Quarks and Gluons with CMS Open Data*, *Phys.Rev.D* **106** (5, 2022) 094021, [2205.04459].

[739] B. Lieberman, J. Choma, S.-E. Dahbi, B. Mellado and X. Ruan, *An investigation of over-training within semi-supervised machine learning models in the search for heavy resonances at the LHC*, in *65th Annual Conference of the South African Institute of Physics*, 9, 2021. 2109.07287.

[740] S.-e. Dahbi, J. Choma, B. Mellado, G. Mokgatitswane, X. Ruan, T. Celik et al., *Machine learning approach for the search of resonances with topological features at the Large Hadron Collider*, *Int.J.Mod.Phys.A* **37** (11, 2020) 2150241, [2011.09863].

[741] J. Brewer, J. Thaler and A. P. Turner, *Data-driven quark and gluon jet modification in heavy-ion collisions*, 2008.08596.

[742] O. Amram and C. M. Suarez, *Tag N' Train: A Technique to Train Improved Classifiers on Unlabeled Data*, 2002.12376. 9

[743] ATLAS Collaboration, *Dijet resonance search with weak supervision using 13 TeV pp collisions in the ATLAS detector*, 2005.02983. 9, 11

[744] E. M. Metodiev and J. Thaler, *Jet Topics: Disentangling Quarks and Gluons at Colliders*, *Phys. Rev. Lett.* **120** (2018) 241602, [1802.00008].

[745] P. T. Komiske, E. M. Metodiev and J. Thaler, *An operational definition of quark and gluon jets*, *JHEP* **11** (2018) 059, [1809.01140].

[746] T. Cohen, M. Freytsis and B. Ostdiek, *(Machine) Learning to Do More with Less*, 1706.09451.

[747] M. Borisyak and N. Kazeev, *Machine Learning on data with sPlot background subtraction*, 1905.11719.

[748] J. H. Collins, K. Howe and B. Nachman, *Extending the search for new resonances with machine learning*, *Phys. Rev.* **D99** (2019) 014038, [1902.02634]. 9

[749] J. H. Collins, K. Howe and B. Nachman, *Anomaly Detection for Resonant New Physics with Machine Learning*, *Phys. Rev. Lett.* **121** (2018) 241803, [1805.02664]. 9

[750] E. M. Metodiev, B. Nachman and J. Thaler, *Classification without labels: Learning from mixed samples in high energy physics*, *JHEP* **10** (2017) 174, [1708.02949].

[751] L. M. Dery, B. Nachman, F. Rubbo and A. Schwartzman, *Weakly Supervised Classification in High Energy Physics*, *JHEP* **05** (2017) 145, [1702.00414]. 5

[752] A. Abdelhaq, P. Piantadosi and F. Quevedo, *Rediscovering the Standard Model with AI*, 2508.04923. 5, 11

[753] S. Chowdhury, A. Chakraborty and S. Dutta, *Probes of Anomalous Events at LHC with Self-Organizing Maps*, 2503.09247. 9

[754] S. Katel, H. Li, Z. Zhao, F. Mokhtar, J. Duarte and R. Kansal, *Learning Symmetry-Independent Jet Representations via Jet-Based Joint Embedding Predictive Architecture*, in *38th conference on Neural Information Processing Systems*, 12, 2024. 2412.05333.

[755] L. R. Sheldon, D. S. Rankin and P. Harris, *MACK: Mismodeling Addressed with Contrastive Knowledge*, *SciPost Phys.* **18** (10, 2024) 150, [2410.13947].

[756] J. Lu, S. Liu, D. Kobylianski, E. Dreyer, E. Gross and S. Liang, *PASCL: Supervised Contrastive Learning with Perturbative Augmentation for Particle Decay Reconstruction*, *Mach.Learn.Sci.Tech.* **5** (2, 2024) 045028, [2402.11538].

[757] T. Kishimoto, M. Morinaga, M. Saito and J. Tanaka, *Pre-training strategy using real particle collision data for event classification in collider physics*, in *37th Conference on Neural Information Processing Systems*, 12, 2023. 2312.06909.

[758] O. Kitouni, N. Nolte, S. Trifinopoulos, S. Kantamneni and M. Williams, *NuCLR: Nuclear Co-Learned Representations*, 2306.06099.

[759] Y. Huang, D. Torbunov, B. Viren, H. Yu, J. Huang, M. Lin et al., *Unsupervised Domain Transfer for Science: Exploring Deep Learning Methods for Translation between LArTPC Detector Simulations with Differing Response Models*, *Mach.Learn.Sci.Tech.* **5** (4, 2023) 045021, [2304.12858].

[760] B. M. Dillon, G. Kasieczka, H. Olischlager, T. Plehn, P. Sorrenson and L. Vogel, *Symmetries, Safety, and Self-Supervision*, *SciPost Phys.* **12** (8, 2021) 188, [2108.04253].

[761] J. N. Howard, S. Mandt, D. Whiteson and Y. Yang, *Foundations of a Fast, Data-Driven, Machine-Learned Simulator*, *Sci.Rep.* **12** (1, 2021) 7567, [2101.08944]. 8, 10

[762] T. Cai, J. Cheng, K. Craig and N. Craig, *Linearized Optimal Transport for Collider Events*, 2008.08604. 5

[763] B. M. Dillon, D. A. Faroughy and J. F. Kamenik, *Uncovering latent jet substructure*, *Phys. Rev.* **D100** (2019) 056002, [1904.04200]. 9

[764] B. M. Dillon, D. A. Faroughy, J. F. Kamenik and M. Szewc, *Learning the latent structure of collider events*, 2005.12319. 9

[765] P. T. Komiske, E. M. Metodiev and J. Thaler, *Metric Space of Collider Events*, *Phys. Rev. Lett.* **123** (2019) 041801, [1902.02346]. 5

[766] L. Mackey, B. Nachman, A. Schwartzman and C. Stansbury, *Fuzzy Jets*, *JHEP* **06** (2016) 010, [1509.02216]. 5

[767] B. M. Dillon and M. Spannowsky, *Theory-informed neural networks for particle physics*, 2507.13447. 5

[768] J. B. Baretz, M. Fieg, V. Ganesh, A. Ghosh, V. Knapp-Perez, J. Rudolph et al., *Towards AI-assisted Neutrino Flavor Theory Design*, 2506.08080.

[769] M. Zeng, *Reinforcement Learning and Metaheuristics for Feynman Integral Reduction*, 2504.16045. 11

[770] G. Angloher et al., *Optimal operation of cryogenic calorimeters through deep reinforcement learning*, *Comput.Softw.Big Sci.* **8** (11, 2023) 10, [2311.15147].

[771] D. Alvestad, A. Rothkopf and D. Sexty, *Lattice real-time simulations with learned optimal kernels*, *Phys.Rev.D* **109** (10, 2023) L031502, [2310.08053]. 7

[772] A. Dersy, M. D. Schwartz and X. Zhang, *Simplifying Polylogarithms with Machine Learning*, *Int.J.Data Sci.Math.Sci.* **1** (6, 2022) 135, [2206.04115]. 6

[773] A. Windisch, T. Gallien and C. Schwarzlmueller, *A machine learning pipeline for autonomous numerical analytic continuation of Dyson-Schwinger equations*, vol. 258, p. 09003, 12, 2021. 2112.13011. DOI.

[774] K. Cranmer, M. Drnevich, S. Macaluso and D. Pappadopulo, *Reframing Jet Physics with New Computational Methods*, *EPJ Web Conf.* **251** (5, 2021) 03059, [2105.10512].

[775] T. R. Harvey and A. Lukas, *Particle Physics Model Building with Reinforcement Learning*, *JHEP* **08** (3, 2021) 161, [2103.04759].

[776] J. S. John et al., *Real-time Artificial Intelligence for Accelerator Control: A Study at the Fermilab Booster*, *Phys.Rev.Accel.Beams* **24** (11, 2020) 104601, [2011.07371].

[777] J. Brehmer, S. Macaluso, D. Pappadopulo and K. Cranmer, *Hierarchical clustering in particle physics through reinforcement learning*, *34th Conference on Neural Information Processing Systems* (11, 2020) , [2011.08191].

[778] S. Carrazza and F. A. Dreyer, *Jet grooming through reinforcement learning*, *Phys. Rev. D* **100** (2019) 014014, [1903.09644]. 5, 6

[779] B. B. Le and D. Keller, *Compton Form Factor Extraction using Quantum Deep Neural Networks*, 2504.15458. 5

[780] K. Pyretzidis, J. J. M. de Lejarza and G. Rodrigo, *Unlocking Multi-Dimensional Integration with Quantum Adaptive Importance Sampling*, 2506.19965. 9

[781] H.-X. Yin, Z.-Y. Hu, H.-H. Zeng, J.-B. Guan and J.-k. Wang, *Application of quantum machine learning using variational quantum classifier in accelerator physics*, 6, 2025. 2506.06662.

[782] A. Bal, M. Klute, B. Maier, M. Oughton, E. Pezone and M. Spannowsky, *1 Particle - 1 Qubit: Particle Physics Data Encoding for Quantum Machine Learning*, 2502.17301.

[783] A. Hammad, M. M. Nojiri and M. Yamazaki, *Quantum similarity learning for anomaly detection*, *JHEP* **02** (2025) 081, [2411.09927]. 9

[784] J. L. Scott, Z. Dong, T. Kim, K. Kong and M. Park, *Hybrid quantum-classical approach for combinatorial problems at hadron colliders*, 2410.22417.

[785] J.-C. Yang, S. Zhang and C.-X. Yue, *A novel quantum machine learning classifier to search for new physics*, 2410.18847. 10

[786] R. Nelakurti and C. Hill, *Evaluating Modifications to Classifiers for Identification of Higgs Bosons*, 2409.10902.

[787] S. Zhang, K.-X. Chen and J.-C. Yang, *Detect anomalous quartic gauge couplings at muon colliders with quantum kernel k-means*, *Eur.Phys.J.C* **85** (9, 2024) 378, [2409.07010]. 9

[788] J. Lazar, S. G. Olavarrieta, G. Gatti, C. A. Argüelles and M. Sanz, *New Pathways in Neutrino Physics via Quantum-Encoded Data Analysis*, 2402.19306.

[789] Y.-A. Chen and K.-F. Chen, *Jet Discrimination with Quantum Complete Graph Neural Network*, *Phys.Rev.D* **111** (3, 2024) 016020, [2403.04990].

[790] S. Hoque, H. Jia, A. Abhishek, M. Fadaie, J. Q. Toledo-Marín, T. Vale et al., *CaloQVAE : Simulating high-energy particle-calorimeter interactions using hybrid quantum-classical generative models*, *Eur.Phys.J.C* **84** (12, 2023) 1244, [2312.03179]. 8

[791] F. Rehm, S. Vallecorsa, K. Borras, M. Grossi, D. Kruecker and V. Varo, *Precise Image Generation on Current Noisy Quantum Computing Devices*, *Quantum Sci.Technol.* **9** (7, 2023) 015009, [2307.05253].

[792] J. Schuhmacher, L. Boggia, V. Belis, E. Puljak, M. Grossi, M. Pierini et al., *Unravelling physics beyond the standard model with classical and quantum anomaly detection*, *Mach.Learn.Sci.Tech.* **4** (1, 2023) 045031, [2301.10787]. 9

[793] K. A. Woźniak, V. Belis, E. Puljak, P. Barkoutsos, G. Dissertori, M. Grossi et al., *Quantum anomaly detection in the latent space of proton collision events at the LHC*, *Commun.Phys.* **7** (1, 2023) 334, [2301.10780].

[794] A. Rousselot and M. Spannowsky, *Generative Invertible Quantum Neural Networks*, *SciPost Phys.* **16** (2, 2023) 146, [2302.12906]. 8

[795] P. Duckett, G. Facini, M. Jastrzebski, S. Malik, T. Scanlon and S. Rettie, *Reconstructing charged particle track segments with a quantum-enhanced support vector machine*, *Phys.Rev.D* **109** (12, 2022) 052002, [2212.07279].

[796] J. Y. Araz and M. Spannowsky, *Quantum-probabilistic Hamiltonian learning for generative modelling & anomaly detection*, *Phys.Rev.A* **108** (11, 2022) 6, [2211.03803]. 9

[797] M. C. Peixoto, N. F. Castro, M. Crispim Romão, M. G. J. a. Oliveira and I. Ochoa, *Fitting a Collider in a Quantum Computer: Tackling the Challenges of Quantum Machine Learning for Big Datasets*, *Front.Artif.Intell.* **6** (11, 2022) 1268852, [2211.03233].

[798] S. Alvi, C. Bauer and B. Nachman, *Quantum Anomaly Detection for Collider Physics*, *JHEP* **02** (6, 2022) 220, [2206.08391]. 9

[799] A. Delgado and K. E. Hamilton, *Unsupervised Quantum Circuit Learning in High Energy Physics*, *Phys.Rev.D* **106** (3, 2022) 096006, [2203.03578].

[800] J. Y. Araz and M. Spannowsky, *Classical versus Quantum: comparing Tensor Network-based Quantum Circuits on LHC data*, *Phys.Rev.A* **106** (2, 2022) 062423, [2202.10471].

[801] S. Abel, J. C. Criado and M. Spannowsky, *Completely Quantum Neural Networks*, *Phys.Rev.A* **106** (2, 2022) 022601, [2202.11727].

[802] A. Gianelle, P. Koppenburg, D. Lucchesi, D. Nicotra, E. Rodrigues, L. Sestini et al., *Quantum Machine Learning for b-jet identification*, *JHEP* **08** (2, 2022) 014, [2202.13943].

[803] V. S. Ngairangbam, M. Spannowsky and M. Takeuchi, *Anomaly detection in high-energy physics using a quantum autoencoder*, *Phys.Rev.D* **105** (12, 2021) 095004, [2112.04958]. 9

[804] M. Kim, P. Ko, J.-h. Park and M. Park, *Leveraging Quantum Annealer to identify an Event-topology at High Energy Colliders*, 2111.07806.

[805] C. Bravo-Prieto, J. Baglio, M. Cè, A. Francis, D. M. Grabowska and S. Carrazza, *Style-based quantum generative adversarial networks for Monte Carlo events*, *Quantum* **6** (10, 2021) 777, [2110.06933]. 8

[806] J. Y. Araz and M. Spannowsky, *Quantum-inspired event reconstruction with Tensor Networks: Matrix Product States*, *JHEP* **08** (2021) 112, [2106.08334].

[807] V. Belis, S. González-Castillo, C. Reissel, S. Vallecorsa, E. F. Combarro, G. Dissertori et al., *Higgs analysis with quantum classifiers*, in *25th International Conference on Computing in High-Energy and Nuclear Physics*, vol. 251, p. 03070, 4, 2021. 2104.07692. DOI.

[808] S. L. Wu et al., *Application of Quantum Machine Learning using the Quantum Kernel Algorithm on High Energy Physics Analysis at the LHC*, *Phys.Rev.Res.* **3** (4, 2021) 033221, [2104.05059].

[809] J. Heredge, C. Hill, L. Hollenberg and M. Sevior, *Quantum Support Vector Machines for Continuum Suppression in B Meson Decays*, *Comput.Softw.Big Sci.* **5** (3, 2021) 27, [2103.12257].

[810] A. Blance and M. Spannowsky, *Unsupervised Event Classification with Graphs on Classical and Photonic Quantum Computers*, *JHEP* **08** (3, 2021) 170, [2103.03897]. 9

[811] S. Y.-C. Chen, T.-C. Wei, C. Zhang, H. Yu and S. Yoo, *Hybrid Quantum-Classical Graph Convolutional Network*, 2101.06189.

[812] S. L. Wu et al., *Application of Quantum Machine Learning using the Quantum Variational Classifier Method to High Energy Physics Analysis at the LHC on IBM Quantum Computer Simulator and Hardware with 10 qubits*, *J.Phys.G* **48** (12, 2020) 125003, [2012.11560].

[813] K. Terashi, M. Kaneda, T. Kishimoto, M. Saito, R. Sawada and J. Tanaka, *Event Classification with Quantum Machine Learning in High-Energy Physics*, 2002.09935.

[814] A. Blance and M. Spannowsky, *Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier*, 2010.07335.

[815] A. Zlokapa, A. Mott, J. Job, J.-R. Vlimant, D. Lidar and M. Spiropulu, *Quantum adiabatic machine learning with zooming*, 1908.04480.

[816] A. Mott, J. Job, J. R. Vlimant, D. Lidar and M. Spiropulu, *Solving a Higgs optimization problem with quantum annealing for machine learning*, *Nature* **550** (2017) 375–379. 5

[817] R. Das, G. Kasieczka and D. Shih, *Feature Selection with Distance Correlation*, *Phys.Rev.D* **109** (11, 2022) 054009, [2212.00046]. 5, 7

[818] T. Faucett, J. Thaler and D. Whiteson, *Mapping Machine-Learned Physics into a Human-Readable Space*, 2010.11998. 5

[819] S. Qiu, S. Han, X. Ju, B. Nachman and H. Wang, *Parton Labeling without Matching: Unveiling Emergent Labelling Capabilities in Regression Models*, *Eur.Phys.J.C* **83** (4, 2023) 622, [2304.09208]. 5, 7

[820] T. Finke, M. Krämer, A. Mück and J. Tönshoff, *Learning the language of QCD jets with transformers*, *JHEP* **06** (3, 2023) 184, [2303.07364]. 5, 8

[821] F. Sforza and V. Lippi, *Support vector machine classification on a biased training*

set: Multi-jet background rejection at hadron colliders, *Nucl. Instrum. Meth. A* **722** (2013) 11–19, [1407.0317]. 5

[822] J. Y. Araz and M. Spannowsky, *Combine and Conquer: Event Reconstruction with Bayesian Ensemble Neural Networks*, *JHEP* **04** (2021) 296, [2102.01078]. 5, 11

[823] M. Algren, T. Golling, F. A. Di Bello and C. Pollard, *Mind the Gap: Navigating Inference with Optimal Transport Maps*, 2507.08867. 5, 9, 10

[824] S. Bright-Thonney, P. Harris, P. McCormack and S. Rothman, *Chained Quantile Morphing with Normalizing Flows*, 2309.15912. 8

[825] ATLAS Collaboration, *Measurements of multijet event isotropies using optimal transport with the ATLAS detector*, *JHEP* **10** (5, 2023) 060, [2305.16930].

[826] L. Gouskos, F. Iemmi, S. Liechti, B. Maier, V. Mikuni and H. Qu, *Optimal transport for a global event description at high-intensity hadron colliders*, *Phys.Rev.D* **108** (11, 2022) 096003, [2211.02029].

[827] T. Manole, P. Bryant, J. Alison, M. Kuusela and L. Wasserman, *Background Modeling for Double Higgs Boson Production: Density Ratios and Optimal Transport*, 2208.02807.

[828] T. Cai, J. Cheng, K. Craig and N. Craig, *Which Metric on the Space of Collider Events?*, *Phys.Rev.D* **105** (11, 2021) 076003, [2111.03670].

[829] C. Pollard and P. Windischhofer, *Transport away your problems: Calibrating stochastic simulations with optimal transport*, *Nucl.Instrum.Meth.A* **1027** (7, 2021) 166119, [2107.08648]. 6

[830] M. C. Romao, N. Castro, J. Milhano, R. Pedro and T. Vale, *Use of a Generalized Energy Mover's Distance in the Search for Rare Phenomena at Colliders*, 2004.09360. 5, 9, 10

[831] N. Clarke Hall and N. Konstantinidis, *Robust anomaly triggers with \textscDecADe*, 2508.10224. 6, 7, 9

[832] F. I. Giasemis, *Real-Time Analysis of Unstructured Data with Machine Learning on Heterogeneous Architectures*, other thesis, 8, 2025.

[833] V. Kladov, J. Messchendorp and J. Ritman, *Real-time calibrations for future detectors at FAIR*, in *8th FAIR next generation scientists workshop 2024*, 5, 2025. 2505.17781. 6

[834] M. Bileska, *Design and FPGA Implementation of WOMBAT: A Deep Neural Network Level-1 Trigger System for Jet Substructure Identification and Boosted $H \to b\bar{b}$ Tagging at the CMS Experiment*, other thesis, 5, 2025. 6

[835] C. Krause, D. Wang and R. Winterhalder, *BitHEP – The Limits of Low-Precision ML in HEP*, 2504.03387.

[836] V. Kholoimov, B. K. Jashal, A. Oyanguren, V. Svintozelskyi and J. Zhuo, *A Downstream and vertexing algorithm for Long Lived Particles (LLP) selection at the first High-level trigger (HLT1) of LHCb*, *Comput.Softw.Big Sci.* **9** (3, 2025) 10, [2503.13092].

[837] D. Meier, W. Helml, T. Otto, B. Sick, J. Viefhaus and G. Hartmann, *Reconstructing Time-of-Flight Detector Values of Angular Streaking Using Machine Learning*, *Phys.Rev.Accel.Beams* **28** (1, 2025) 074601, [2501.08966].

[838] S. Ragoni, J. Seger, C. Anson and D. Tlusty, *Machine learning opportunities for online and offline tagging of photo-induced and diffractive events in continuous readout experiments*, 2410.06983.

[839] U. Pratiush, A. Houston, S. V. Kalinin and G. Duscher, *Implementing dynamic high-performance computing supported workflows on Scanning Transmission Electron Microscope*, 2406.11018.

[840] C. Bierlich, A. Buckley, J. Butterworth, C. Gutschow, L. Lonnblad, T. Procter et al., *Robust Independent Validation of Experiment and Theory: Rivet version 4 release note*, *SciPost Phys.Codeb.* **36** (4, 2024) 1, [2404.15984].

[841] M. Ivanov, M. Ivanov and G. Eulisse, *RootInteractive tool for multidimensional statistical analysis, machine learning and analytical model validation*, *EPJ Web Conf.* **295** (2024) 06019, [2403.19330].

[842] ALICE Collaboration, *Software Compensation for Highly Granular Calorimeters using Machine Learning*, *JINST* **19** (2024) P04037, [2403.04632].

[843] A. Held, E. Kauffman, O. Shadura and A. Wightman, *Physics analysis for the HL-LHC: concepts and pipelines in practice with the Analysis Grand Challenge*, vol. 295, p. 06016, 1, 2024. 2401.02766. DOI.

[844] E. Kauffman, A. Held and O. Shadura, *Machine Learning for Columnar High Energy Physics Analysis*, vol. 295, p. 08011, 1, 2024. 2401.01802. DOI.

[845] A. Bal, T. Brandes, F. Iemmi, M. Klute, B. Maier, V. Mikuni et al., *Distilling particle knowledge for fast reconstruction at high-energy physics experiments*, *Mach.Learn.Sci.Tech.* **5** (11, 2023) 025033, [2311.12551].

[846] F. A. Di Bello et al., *Configurable calorimeter simulation for AI applications*, *Mach.Learn.Sci.Tech.* **4** (3, 2023) 035042, [2303.02101].

[847] DPHEP Collaboration, *Data Preservation in High Energy Physics – DPHEP Global Report 2022*, *Eur.Phys.J.C* **83** (2, 2023) 795, [2302.03583].

[848] R. Tyson, G. Gavalian, D. Ireland and B. McKinnon, *Deep learning level-3 electron trigger for CLAS12*, *Comput. Phys. Commun.* **290** (2023) 108783, [2302.07635].

[849] Y.-C. Guo, F. Feng, A. Di, S.-Q. Lu and J.-C. Yang, *MLAnalysis: An open-source program for high energy physics analyses*, *Comput.Phys.Commun.* **294** (5, 2023) 108957, [2305.00964].

[850] J. Duarte et al., *FAIR AI Models in High Energy Physics*, *Mach.Learn.Sci.Tech.* **4** (12, 2022) 045062, [2212.05081].

[851] R. B. Garg, E. Hofgard, L. Tompkins and H. Gray, *Exploration of different parameter optimization algorithms within the context of ACTS software framework*, 2211.00764. 7

[852] P.A.N.D.A. Collaboration, *Deep machine learning for the PANDA software trigger*, *Eur. Phys. J. C* **83** (2023) 337, [2211.15390]. 11

[853] M. Saito, T. Kishimoto, Y. Kaneta, T. Itoh, Y. Umeda, J. Tanaka et al., *Event Classification with Multi-step Machine Learning*, *EPJ Web Conf.* **251** (2021) 03036, [2106.02301].

[854] S. Amrouche et al., *The Tracking Machine Learning challenge : Throughput phase*, *Comput.Softw.Big Sci.* **7** (5, 2021) 1, [2105.01160].

[855] C. Mahesh, K. Dona, D. W. Miller and Y. Chen, *Towards an Interpretable Data-driven Trigger System for High-throughput Physics Facilities*, in *34th Conference on Neural Information Processing Systems*, 4, 2021. 2104.06622.

[856] F. Rehm, S. Vallecorsa, V. Saletore, H. Pabst, A. Chaibi, V. Codreanu et al., *Reduced Precision Strategies for Deep Learning: A High Energy Physics Generative Adversarial Network Use Case*, 2103.10142. 8

[857] D. Bourgeois, C. Fitzpatrick and S. Stahl, *Using holistic event information in the trigger*, 1808.00711.

[858] D. W. III, T. Q. Nguyen, D. Anderson, R. Castello, M. Pierini, M. Spiropulu et al., *Deep topology classifiers for a more efficient trigger selection at the LHC*, 2017.

[859] V. V. Gligorov and M. Williams, *Efficient, reliable and fast high-level triggering using a bonsai boosted decision tree*, *JINST* **8** (2013) P02013, [1210.6861].

[860] G. C. Strong, *On the impact of modern deep-learning techniques to the performance and time-requirements of classification models in experimental high-energy physics*, 2002.01427. 6

[861] B. T. Carlson, S. T. Roche, M. Hemmett and T. M. Hong, *Ring-based ML calibration with in situ pileup correction for real-time jet triggers*, 2507.16686. 6

[862] C. Sun, Z. Que, V. Loncar, W. Luk and M. Spiropulu, *da4ml: Distributed Arithmetic for Real-time Neural Networks on FPGAs*, 2507.04535.

[863] B. Maček, *Learning Before Filtering: Real-Time Hardware Learning at the Detector Level*, 2506.11981.

[864] C. Sun, J. Ngadiuba, M. Pierini and M. Spiropulu, *Fast Jet Tagging with MLP-Mixers on FPGAs*, *Mach.Learn.Sci.Tech.* **6** (3, 2025) 035025, [2503.03103].

[865] MODE Collaboration, *Neuromorphic Readout for Hadron Calorimeters*, *Particles* **8** (2, 2025) 52, [2502.12693]. 6

[866] F. I. Giasemis, V. Lončar, B. Granado and V. V. Gligorov, *Comparative Analysis of FPGA and GPU Performance for Machine Learning-Based Track Reconstruction at LHCb*, 2502.02304.

[867] J. Kvapil et al., *Intelligent experiments through real-time AI: Fast Data Processing and Autonomous Detector Control for sPHENIX and future EIC detectors*, *PoS* **ICHEP2024** (2025) 1033, [2501.04845].

[868] H. Jia, A. Dave, J. Gonski and R. Herbst, *Analysis of Hardware Synthesis Strategies for Machine Learning in Collider Trigger and Data Acquisition*, 2411.11678.

[869] CMS Collaboration, *Performance of the CMS high-level trigger during LHC Run 2*, *JINST* **19** (10, 2024) P11021, [2410.17038].

[870] A. Badea et al., *Intelligent Pixel Detectors: Towards a Radiation Hard ASIC with On-Chip Machine Learning in 28 nm CMOS*, in *42nd International Conference on High Energy Physics*, vol. ICHEP2024, p. 1074, 10, 2024. 2410.02945. DOI.

[871] P. Serhiayenka, S. Roche, B. Carlson and T. M. Hong, *Nanosecond hardware regression trees in FPGA at the LHC*, *Nucl.Instrum.Meth.A* **1072** (9, 2024) 170209, [2409.20506].

[872] L. Borella, A. Coppi, J. Pazzini, A. Stanco, M. Trenti, A. Triossi et al., *Ultra-low latency quantum-inspired machine learning predictors implemented on FPGA*, 2409.16075.

[873] T. Zhu, M. Jin and C. A. Argüelles, *Comparison of Geometrical Layouts for Next-Generation Large-volume Cherenkov Neutrino Telescopes*, *JINST* **20** (7, 2024) P05001, [2407.19010].

[874] E. E. Los, C. Arran, E. Gerstmayr, M. J. V. Streeter, Z. Najmudin, C. P. Ridgers et al., *A Bayesian Framework to Investigate Radiation Reaction in Strong Fields*, *High Power Laser Sci.Eng.* **13** (6, 2024) e25, [2406.19420].

[875] B. Parpillon et al., *Smart Pixels: In-pixel AI for on-sensor data filtering*, 2406.14860.

[876] E. Tiras, M. Tas, D. Kizilkaya, M. A. Yagiz and M. Kandemir, *Comprehensive Machine Learning Model Comparison for Cherenkov and Scintillation Light Separation due to Particle Interactions*, 2406.09191.

[877] S. Bähr et al., *The Neural Network First-Level Hardware Track Trigger of the Belle II Experiment*, *Nucl.Instrum.Meth.A* **1073** (2, 2024) 170279, [2402.14962].

[878] CMS Collaboration, *Portable acceleration of CMS computing workflows with coprocessors as a service*, *Comput.Softw.Big Sci.* **8** (2, 2024) 17, [2402.15366].

[879] J. Dickinson et al., *Smartpixels: Towards on-sensor inference of charged particle track parameters and uncertainties*, 2312.11676. 11

[880] B. Delaney, N. Schulte, G. Ciezarek, N. Nolte, M. Williams and J. Albrecht, *Applications of Lipschitz neural networks to the Run 3 LHCb trigger system*, *EPJ Web Conf.* **295** (12, 2023) 09005, [2312.14265].

[881] CMS Collaboration, *Testing a Neural Network for Anomaly Detection in the CMS Global Trigger Test Crate during Run 3*, in *Topical Workshop on Electronics for Particle Physics*, vol. 19, p. C03029, 12, 2023. 2312.10009. DOI. 9

[882] S. Lin, S. Ning, H. Zhu, T. Zhou, C. L. Morris, S. Clayton et al., *Neural Network Methods for Radiation Detectors and Imaging*, 2311.05726.

[883] M. Jin, Y. Hu and C. A. Argüelles, *Two Watts is All You Need: Enabling In-Detector Real-Time Machine Learning for Neutrino Telescopes Via Edge Computing*, *JCAP* **06** (11, 2023) 026, [2311.04983].

[884] G. Grosso, N. Lai, M. Migliorini, J. Pazzini, A. Triossi, M. Zanetti et al., *Triggerless data acquisition pipeline for Machine Learning based statistical anomaly detection*, *EPJ Web Conf.* **295** (11, 2023) 02033, [2311.02038]. 9

[885] J. Yoo et al., *Smart pixel sensors: towards on-sensor filtering of pixel clusters with deep learning*, *Mach.Learn.Sci.Tech.* **5** (10, 2023) 035047, [2310.02474].

[886] N. Schulte, B. R. Delaney, N. Nolte, G. M. Ciezarek, J. Albrecht and M. Williams, *Development of the Topological Trigger for LHCb Run 3*, 2306.09873.

[887] M. Yaary, U. Barron, L. P. Domínguez, B. Chen, L. Barak, E. Etzion et al., *Comparing machine learning models for tau triggers*, *Sci.Rep.* **15** (6, 2023) 21832, [2306.06743].

[888] R. Okabe, S. Xue, J. Yu, T. Liu, B. Forget, S. Jegelka et al., *Tetris-inspired detector with neural network for radiation mapping*, vol. 15, p. 3061, 2, 2023. 2302.07099. DOI.

[889] A. Coccaro, F. A. Di Bello, S. Giagu, L. Rambelli and N. Stocchetti, *Fast Neural Network Inference on FPGAs for Triggering on Long-Lived Particles at Colliders*, *Mach.Learn.Sci.Tech.* **4** (7, 2023) 045040, [2307.05152].

[890] R. Herbst, R. Coffee, N. Fronk, K. Kim, K. Kim, L. Ruckman et al., *Implementation of a framework for deploying AI inference engines in FPGAs*, 2305.19455.

[891] T. Cai, K. Herner, T. Yang, M. Wang, M. A. Flechas, P. Harris et al., *Accelerating Machine Learning Inference with GPUs in ProtoDUNE Data Processing*, *Comput.Softw.Big Sci.* **7** (1, 2023) 11, [2301.04633].

[892] H. Meyer zu Theenhausen, B. von Krosigk and J. S. Wilson, *Neural-network-based level-1 trigger upgrade for the SuperCDMS experiment at SNOLAB*, *JINST* **18** (2023) P06012, [2212.07864].

[893] D. J. Kösters et al., *Benchmarking energy consumption and latency for neuromorphic computing in condensed matter and particle physics*, *APL Mach. Learn.* **1** (2023) 016101, [2209.10481].

[894] B. Carlson, Q. Bayer, T. M. Hong and S. Roche, *Nanosecond machine learning regression with deep boosted decision trees in FPGA for high energy physics*, *JINST* **17** (7, 2022) P09039, [2207.05602].

[895] E. E. Khoda et al., *Ultra-low latency recurrent neural network inference on FPGAs for physics applications with hls4ml*, *Mach.Learn.Sci.Tech.* **4** (7, 2022) 025004, [2207.00559].

[896] A. Butter, S. Diefenbacher, G. Kasieczka, B. Nachman, T. Plehn, D. Shih et al., *Ephemeral Learning – Augmenting Triggers with Online-Trained Normalizing Flows*, *SciPost Phys.* **13** (2, 2022) 087, [2202.09375]. 8

[897] Y.-J. Jwa, G. D. Guglielmo, L. P. Carloni and G. Karagiorgi, *Accelerating Deep Neural Networks for Real-time Data Selection for High-resolution Imaging Particle Detectors*, in *2019 New York Scientific Data Summit: Data-Driven Discovery in Science and Industry*, 6, 2019. 2201.04740. DOI.

[898] E. Govorkova et al., *Autoencoders on FPGAs for real-time, unsupervised new physics detection at 40 MHz at the Large Hadron Collider*, *Nature Mach.Intell.* **4** (8, 2021) 154, [2108.03986]. 9

[899] M. Migliorini, J. Pazzini, A. Triossi, M. Zanetti and A. Zucchetta, *Muon trigger with fast Neural Networks on FPGA, a demonstrator*, *J.Phys.Conf.Ser.* **2374** (5, 2021) 012099, [2105.04428].

[900] G. Di Guglielmo et al., *A reconfigurable neural network ASIC for detector front-end data compression at the HL-LHC*, *IEEE Trans.Nucl.Sci.* **68** (5, 2021) 2179, [2105.01683].

[901] T. M. Hong, B. T. Carlson, B. R. Eubanks, S. T. Racz, S. T. Roche, J. Stelzer et al., *Nanosecond machine learning event classification with boosted decision trees in FPGA for high energy physics*, *JINST* **16** (4, 2021) P08016, [2104.03408].

[902] T. Teixeira, L. Andrade and J. M. de Seixas, *Sparse Deconvolution Methods for Online Energy Estimation in Calorimeters Operating in High Luminosity Conditions*, *JINST* **16** (3, 2021) P09008, [2103.12467].

[903] B. Hawks, J. Duarte, N. J. Fraser, A. Pappalardo, N. Tran and Y. Umuroglu, *Ps and Qs: Quantization-aware pruning for efficient low latency neural network inference*, *Front.Artif.Intell.* **4** (2, 2021) 676564, [2102.11289].

[904] T. Aarrestad et al., *Fast convolutional neural networks on FPGAs with hls4ml*, *Mach.Learn.Sci.Tech.* **2** (1, 2021) 045015, [2101.05108].

[905] M. Rossi, S. Carrazza and J. M. Cruz-Martinez, *PDFFlow: hardware accelerating parton density access*, 2012.08221. 7

[906] D. S. Rankin et al., *FPGAs-as-a-Service Toolkit (FaaST)*, *2020 IEEE/ACM International Workshop on Heterogeneous High-performance Reconfigurable Computing (H2RC)* (10, 2020) 38, [2010.08556].

[907] S. Carrazza, J. M. Cruz-Martinez and M. Rossi, *PDFFlow: parton distribution functions on GPU*, *Comput.Phys.Commun.* **264** (9, 2020) 107995, [2009.06635].

[908] L. R. M. Mohan, A. Marshall, S. Maddrell-Mander, D. O'Hanlon, K. Petridis, J. Rademacker et al., *Studying the potential of Graphcore IPUs for applications in Particle Physics*, 2008.09210.

[909] J. Krupa et al., *GPU coprocessors as a service for deep learning inference in high energy physics*, *Mach.Learn.Sci.Tech.* **2** (7, 2020) 035005, [2007.10359].

[910] S. Summers et al., *Fast inference of Boosted Decision Trees in FPGAs for particle physics*, *JINST* **15** (2020) P05026, [2002.02534].

[911] J. Ngadiuba et al., *Compressing deep neural networks on FPGAs to binary and ternary precision with HLS4ML*, *Mach. Learn.: Sci. Tech.* **2** (2020) 015001, [2003.06308].

[912] J. Duarte et al., *Fast inference of deep neural networks in FPGAs for particle physics*, *JINST* **13** (2018) P07027, [1804.06913]. 6

[913] R. Tyson and G. Gavalian, *Online Electron Reconstruction at CLAS12*, 2507.05274. 6

[914] CMS Collaboration, *Realtime Anomaly Detection at the L1 Trigger of CMS Experiment*, *PoS* **ICHEP2024** (2025) 1025, [2411.19506].

[915] J. Li and H. Sun, *HEP ML Lab: An end-to-end framework for applying machine learning into phenomenology studies*, 2405.02888.

[916] S. Bieringer, G. Kasieczka, J. Kieseler and M. Trabs, *Classifier Surrogates: Sharing AI-based Searches with the World*, *Eur.Phys.J.C* **84** (2, 2024) 972, [2402.15558].

[917] C. Savard, N. Manganelli, B. Holzman, L. Gray, A. Perloff, K. Pedro et al., *Optimizing High Throughput Inference on Graph Neural Networks at Shared Computing Facilities with the NVIDIA Triton Inference Server*, *Comput.Softw.Big Sci.* **8** (12, 2023) 14, [2312.06838].

[918] O. Sunneborn Gudnadottir, D. Gedon, C. Desmarais, K. B. Bernander, R. Sainudiin and R. G. Suarez, *Distributed training and scalability for the particle clustering method UCluster*, *EPJ Web Conf.* **251** (2021) 02054, [2109.00264].

[919] V. Kuznetsov, L. Giommi and D. Bonacorsi, *MLaaS4HEP: Machine Learning as a Service for HEP*, *Comput.Softw.Big Sci.* **5** (7, 2020) 17, [2007.14781]. 6

[920] K. Dimitrova, V. Kozhuharov, R. Nastaev and P. Petkov, *Cluster Reconstruction in Electromagnetic Calorimeters Using Machine Learning Methods*, 2505.24740. 6, 7

[921] L. Vaughan, M. Rakib, S. Patel, F. Rizatdinova, A. Khanov and A. Bagavathi, *PileUp Mitigation at the HL-LHC Using Attention for Event-Wide Context*, 2503.02860.

[922] M. Algren, C. Pollard, J. A. Raine and T. Golling, *Variational inference for pile-up removal at hadron colliders with diffusion models*, *Phys.Rev.D* **111** (10, 2024) 116010, [2410.22074]. 8

[923] K. Lieret, G. DeZoort, D. Chatterjee, J. Park, S. Miao and P. Li, *High Pileup Particle Tracking with Object Condensation*, 12, 2023. 2312.03823.

[924] C. H. Kim, S. Ahn, K. Y. Chae, J. Hooker and G. V. Rogachev, *Restoring original signals from pile-up using deep learning*, *Nucl. Instrum. Meth. A* **1055** (2023) 168492, [2304.14496].

[925] CRESST Collaboration, *Towards an automated data cleaning with deep learning in CRESST*, *Eur. Phys. J. Plus* **138** (2023) 100, [2211.00564].

[926] B. Maier, S. M. Narayanan, G. de Castro, M. Goncharov, C. Paus and M. Schott, *Pile-Up Mitigation using Attention*, *Mach.Learn.Sci.Tech.* **3** (7, 2021) 025012, [2107.02779].

[927] P. T. Komiske, E. M. Metodiev, B. Nachman and M. D. Schwartz, *Pileup Mitigation with Machine Learning (PUMML)*, *JHEP* **12** (2017) 051, [1707.08600]. 6

[928] A. Mishra, M. Seaberg, R. Roussel, F. Poitevin, J. Thayer, D. Ratner et al., *A Start To End Machine Learning Approach To Maximize Scientific Throughput From The LCLS-II-HE*, 2505.23858. 6, 10

[929] K. Dimitrova, V. Kozhuharov and P. Petkov, *Development and Explainability of Models for Machine-Learning-Based Reconstruction of Signals in Particle Detectors*, *Particles* **8** (2025) 48, [2504.17272]. 8

[930] A. De Vita et al., *Hadron Identification Prospects With Granular Calorimeters*, *Particles* **8** (2, 2025) 58, [2502.10817].

[931] M. Borysova, S. Bressler, E. Gross, N. Kakati and D. Zavazieva, *Point Cloud Deep Learning Methods for Particle Shower Reconstruction in the DHCAL*, in *20th International Conference on Calorimetry in Particle Physics*, vol. 320, p. 00025, 12, 2024. 2412.11208. DOI.

[932] ATLAS Collaboration, *Precision calibration of calorimeter signals in the ATLAS experiment using an uncertainty-aware neural network*, 2412.04370.

[933] CMS Collaboration, *Reweighting simulated events using machine-learning techniques in the CMS experiment*, 2411.03023.

[934] N. Akchurin et al., *Vertex Imaging Hadron Calorimetry Using AI/ML Tools*, in *20th International Conference on Calorimetry in Particle Physics*, vol. 320, p. 00026, 8, 2024. 2408.15385. DOI.

[935] T. Britton, M. Goodrich, N. Jarvis, T. Jeske, N. Kalra, D. Lawrence et al., *ML-based Calibration and Control of the GlueX Central Drift Chamber*, *JINST* **19** (3, 2024) C11012, [2403.13823].

[936] R. K. Hashmani, E. Akbaş and M. B. Demirköz, *A Comparison of Deep Learning Models for Proton Background Rejection with the AMS Electromagnetic Calorimeter*, *Mach.Learn.Sci.Tech.* **5** (2, 2024) 045008, [2402.16285].

[937] M. Zdybal, M. Kucharczyk and M. Wolter, *Machine learning based event reconstruction for the MUonE experiment*, *Comput. Sci.* **25** (2024) 25–46, [2402.02913].

[938] M. Kocot, K. Misan, V. Avati, E. Bossini, L. Grzanka and N. Minafra, *Using deep neural networks to improve the precision of fast-sampled particle timing detectors*, 2312.05883.

[939] CMS collaboration, S. Bein, P. Connor, K. Pedro, P. Schleper and M. Wolf, *Refining fast simulation using machine learning*, in *26th International Conference on Computing in High Energy & Nuclear Physics*, vol. 295, p. 09032, 9, 2023. 2309.12919. DOI.

[940] ALPS Collaboration, *A first application of machine and deep learning for background rejection in the ALPS II TES detector*, in *17th Workshop on Axions, WIMPs and WISPs*, 4, 2023. 2304.08406. DOI.

[941] ALICE TPC Collaboration, *Correction of the baseline fluctuations in the GEM-based ALICE TPC*, *JINST* **18** (4, 2023) P11021, [2304.03881].

[942] ATLAS Collaboration, *New techniques for jet calibration with the ATLAS detector*, *Eur.Phys.J.C* **83** (3, 2023) 761, [2303.17312].

[943] H. K. Khozani, Z. Yao and Y. Ye, *Removing Noise From Simulated Events at The Main Drift Chamber of BESIII Using Convolutional Neural Networks*, 2303.12202.

[944] J. A. Raine, M. Leigh, K. Zoch and T. Golling, *ν^2-Flows: Fast and improved neutrino reconstruction in multi-neutrino final states with conditional normalizing flows*, *Phys.Rev.D* **109** (7, 2023) 012005, [2307.02405]. 8

[945] G. Grosso, N. Lai, M. Letizia, J. Pazzini, M. Rando, L. Rosasco et al., *Fast kernel methods for Data Quality Monitoring as a goodness-of-fit test*, *Mach.Learn.Sci.Tech.* **4** (3, 2023) 035029, [2303.05413].

[946] G. Grosso, N. Lai, M. Letizia, J. Pazzini, M. Rando, A. Wulzer et al., *A fast and flexible machine learning approach to data quality monitoring*, in *36th Conference on Neural Information Processing Systems*, 1, 2023. 2301.08917.

[947] B. Schwenker, L. Herzberg, Y. Buch, A. Frey, A. Natochii, S. Vahsen et al., *A neural network for beam background decomposition in Belle II at SuperKEKB*, *Nucl. Instrum. Meth. A* **1049** (2023) 168112, [2301.06170].

[948] H.-G. Lee and J. Park, *Restoring the saturation response of a PMT using pulse shape and artificial neural networks*, *PTEP* **2023** (2023) 053C01, [2302.06170].

[949] G. Aad, T. Calvet, N. Chiedde, R. Faure, E. M. Fortin, L. Laatu et al., *Firmware implementation of a recurrent neural network for the computation of the energy deposited in the liquid argon calorimeter of the ATLAS experiment*, *JINST* **18** (2023) P05017, [2302.07555].

[950] CMS collaboration, V. Guglielmi, *Machine learning approaches for parameter reweighting for MC samples of top quark production in CMS*, *PoS* **ICHEP2022** (11, 2022) 1045, [2211.07355].

[951] P. Ge, X. Huang, M. Saur and L. Sun, *A new method for the q^2 reconstruction in semileptonic decays at LHCb based on machine learning*, *Adv.High Energy Phys.* **2023** (8, 2022) 8127604, [2208.02145].

[952] D. Darulis, R. Tyson, D. G. Ireland, D. I. Glazier, B. McKinnon and P. Pauli, *Machine Learned Particle Detector Simulations*, 2207.11254.

[953] M. Leigh, J. A. Raine and T. Golling, *ν-Flows: conditional neutrino regression*, *SciPost Phys.* **14** (7, 2022) 159, [2207.00664]. 8

[954] CMS collaboration, D. Valsecchi, *Deep learning techniques for energy clustering in the CMS ECAL*, in *20th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI Decoded - Towards Sustainable, Diverse, Performant and Effective Scientific Computing*, vol. 2438, p. 012077, 4, 2022. 2204.10277. DOI.

[955] R. Gambhir, B. Nachman and J. Thaler, *Bias and Priors in Machine Learning*

Calibrations for High Energy Physics, *Phys.Rev.D* **106** (5, 2022) 036011, [2205.05084].

[956] R. Gambhir, B. Nachman and J. Thaler, *Learning Uncertainties the Frequentist Way: Calibration and Correlation in High Energy Physics*, *Phys.Rev.Lett.* **129** (5, 2022) 082001, [2205.03413].

[957] N. Akchurin, J. Damgov, S. Dugad, P. G. C, S. Grönroos, K. Lamichhane et al., *Deep learning applications for quality control in particle detector construction*, 3, 2022. 2203.08969.

[958] S. Qiu, S. Han, X. Ju, B. Nachman and H. Wang, *A Holistic Approach to Predicting Top Quark Kinematic Properties with the Covariant Particle Transformer*, *Phys.Rev.D* **107** (3, 2022) 114029, [2203.05687].

[959] A. Alves and C. H. Yamaguchi, *Reconstruction of Missing Resonances Combining Nearest Neighbors Regressors and Neural Network Classifiers*, *Eur.Phys.J.C* **82** (3, 2022) 746, [2203.03662].

[960] T. Dorigo, S. Guglielmini, J. Kieseler, L. Layer and G. C. Strong, *Deep Regression of Muon Energy with a K-Nearest Neighbor Algorithm*, 2203.02841.

[961] M. Chadeeva and S. Korpachev, *Machine-learning-based prediction of parameters of secondaries in hadronic showers using calorimetric observables*, *JINST* **17** (5, 2022) P10031, [2205.12534].

[962] D. F. Rentería-Estrada, R. J. Hernández-Pinto, G. F. R. Sborlini and P. Zurita, *Reconstructing partonic kinematics at colliders with Machine Learning*, *SciPost Phys.Core* **5** (12, 2021) 049, [2112.05043].

[963] B. Kronheim, M. P. Kuchera, H. B. Prosper and R. Ramanujan, *Implicit Quantile Neural Networks for Jet Simulation and Correction*, 2111.11415.

[964] M. Arratia, D. Britzger, O. Long and B. Nachman, *Reconstructing the Kinematics of Deep Inelastic Scattering with Deep Learning*, *Nucl.Instrum.Meth.A* **1025** (10, 2021) 166164, [2110.05505].

[965] IceCube Collaboration, *Using Convolutional Neural Networks to Reconstruct Energy of GeV Scale IceCube Neutrinos*, vol. 16, p. C09019, 9, 2021. 2109.08152. DOI.

[966] L. Polson, L. Kurchaninov and M. Lefebvre, *Energy reconstruction in a liquid argon calorimeter cell using convolutional neural networks*, *JINST* **17** (9, 2021) P01002, [2109.05124].

[967] M. Diefenthaler, A. Farhat, A. Verbytskyi and Y. Xu, *Deeply Learning Deep Inelastic Scattering Kinematics*, *Eur.Phys.J.C* **82** (8, 2021) 1064, [2108.11638].

[968] N. Akchurin, C. Cowden, J. Damgov, A. Hussain and S. Kunori, *Perspectives on the*

Calibration of CNN Energy Reconstruction in Highly Granular Calorimeters, 2108.10963.

[969] J. Kieseler, *Object condensation: one-stage grid-free multi-object reconstruction in physics detectors, graph and image data*, *Eur. Phys. J. C* **80** (2020) 886, [2002.03605].

[970] N. Akchurin, C. Cowden, J. Damgov, A. Hussain and S. Kunori, *On the Use of Neural Networks for Energy Reconstruction in High-granularity Calorimeters*, *JINST* **16** (7, 2021) P12036, [2107.10207].

[971] J. Kieseler, G. C. Strong, F. Chiandotto, T. Dorigo and L. Layer, *Calorimetric Measurement of Multi-TeV Muons via Deep Regression*, *Eur.Phys.J.C* **82** (7, 2021) 79, [2107.02119].

[972] P. Baldi, L. Blecher, A. Butter, J. Collado, J. N. Howard, F. Keilbach et al., *How to GAN Higher Jet Resolution*, *SciPost Phys.* **13** (12, 2020) 064, [2012.11944].

[973] CMS Collaboration, *A deep neural network for simultaneous estimation of b jet energy and resolution*, 1912.06046.

[974] G. Kasieczka, M. Luchmann, F. Otterpohl and T. Plehn, *Per-Object Systematics using Deep-Learned Calibration*, 2003.11099.

[975] ATLAS Collaboration, *Generalized Numerical Inversion: A Neural Network Approach to Jet Calibration*, Tech. Rep. ATL-PHYS-PUB-2018-013, CERN, Geneva, Jul, 2018.

[976] ATLAS Collaboration, *Simultaneous Jet Energy and Mass Calibrations with Neural Networks*, Tech. Rep. ATL-PHYS-PUB-2020-001, CERN, Geneva, Jan, 2020.

[977] S. Cheong, A. Cukierman, B. Nachman, M. Safdari and A. Schwartzman, *Parametrizing the Detector Response with Neural Networks*, *JINST* **15** (2020) P01030, [1910.03773]. 6

[978] B. Nachman and D. Noll, *FlexCAST: Enabling Flexible Scientific Data Analyses*, 2507.11528. 6

[979] L. Corpe, A. Haddad and M. Goodsell, *Recasting the ATLAS search for displaced hadronic jets in the ATLAS calorimeter with additional jets or leptons using surrogate models*, 2502.10231. 11

[980] M. D. Goodsell, *HackAnalysis 2: A powerful and hackable recasting tool*, 2406.10042.

[981] A. Hammad, M. Park, R. Ramos and P. Saha, *Exploration of Parameter Spaces Assisted by Machine Learning*, *Comput.Phys.Commun.* **293** (7, 2022) 108902, [2207.09959].

[982] B. Kronheim, M. Kuchera, H. Prosper and A. Karbo, *Bayesian Neural Networks for Fast SUSY Predictions*, 2007.04506.

[983] G. Bertone, M. P. Deisenroth, J. S. Kim, S. Liem, R. Ruiz de Austri and M. Welling, *Accelerating the BSM interpretation of LHC data with machine learning*, 1611.02704. 9

[984] S. Caron, J. S. Kim, K. Rolbiecki, R. R. de Austri and B. Stienen, *The BSM-AI project: SUSY-AI–generalizing LHC limits on supersymmetry with machine learning*, *The European Physical Journal C* **77** (2017) 257, [1605.02797]. 6

[985] T. Herrmann, T. Janßen, M. Schenker, S. Schumann and F. Siegert, *Accelerating multijet-merged event generation with neural network matrix element surrogates*, 2506.06203. 6

[986] T. Heimel, N. Huetsch, F. Maltoni, O. Mattelaer, T. Plehn and R. Winterhalder, *The MadNIS Reloaded*, *SciPost Phys.* **17** (11, 2023) 023, [2311.01548]. 8

[987] S. Kaidisch, T. U. Hilger, A. Krassnigg and W. Lucha, *Pole-fitting for complex functions: Enhancing standard techniques by artificial-neural-network classifiers and regressors*, *Comput. Phys. Commun.* **295** (2024) 108998, [2309.08358].

[988] D. Maître and H. Truong, *One-loop matrix element emulation with factorisation awareness*, 2302.04005.

[989] T. Janßen, D. Maître, S. Schumann, F. Siegert and H. Truong, *Unweighting multijet event generation using factorisation-aware neural networks*, *SciPost Phys.* **15** (1, 2023) 107, [2301.13562].

[990] S. Badger, A. Butter, M. Luchmann, S. Pitz and T. Plehn, *Loop Amplitudes from Precision Networks*, *SciPost Phys. Core* **6** (2023) 034, [2206.14831].

[991] A. Alnuqaydan, S. Gleyzer and H. Prosper, *SYMBA: Symbolic Computation of Squared Amplitudes in High Energy Physics with Machine ALearning*, *Mach.Learn.Sci.Tech.* **4** (6, 2022) 015007, [2206.08901].

[992] C. Karl, P. Eller and S. Mertens, *Fast and precise model calculation for KATRIN using a neural network*, *Eur.Phys.J.C* **82** (1, 2022) 439, [2201.04523].

[993] R. Winterhalder, V. Magerya, E. Villa, S. P. Jones, M. Kerner, A. Butter et al., *Targeting Multi-Loop Integrals with Neural Networks*, *SciPost Phys.* **12** (2022) 129, [2112.09145]. 8

[994] K. Danziger, T. Janßen, S. Schumann and F. Siegert, *Accelerating Monte Carlo event generation – rejection sampling using neural network event-weight estimates*, *SciPost Phys.* **12** (9, 2021) 164, [2109.11964]. 9

[995] D. Maître and H. Truong, *A factorisation-aware Matrix element emulator*, *JHEP* **11** (7, 2021) 066, [2107.06625].

[996] J. Aylett-Bullock, S. Badger and R. Moodie, *Optimising simulations for diphoton production at hadron colliders using amplitude neural networks*, *JHEP* **08** (6, 2021) 066, [2106.09474].

[997] D. L. B. Sombillo, Y. Ikeda, T. Sato and A. Hosaka, *Model independent analysis of coupled-channel scattering: a deep learning approach*, *Phys.Rev.D* **104** (5, 2021) 036001, [2105.04898].

[998] D. L. B. Sombillo, Y. Ikeda, T. Sato and A. Hosaka, *Unveiling the pole structure of S-matrix using deep learning*, *Rev.Mex.Fis.Suppl.* **3** (4, 2021) 0308067, [2104.14182].

[999] F. Bury and C. Delaere, *Matrix Element Regression with Deep Neural Networks – breaking the CPU barrier*, *JHEP* **04** (8, 2020) 020, [2008.10949].

[1000] A. Buckley, A. Kvellestad, A. Raklev, P. Scott, J. V. Sparre, J. V. d. Abeele et al., *Xsec: the cross-section evaluation code*, 2006.16273. 9

[1001] F. Bishara and M. Montull, *(Machine) Learning Amplitudes for Faster Event Generation*, *Phys.Rev.D* **107** (12, 2019) L071901, [1912.11055].

[1002] S. Badger and J. Bullock, *Using neural networks for efficient evaluation of high multiplicity scattering amplitudes*, *JHEP* **06** (2020) 114, [2002.07516]. 6

[1003] E. Abasov, L. Dudko, E. Iudin, A. Markina, P. Volkov, G. Vorotnikov et al., *Reconstruction of angular correlations in the associated top quark and the dark matter mediator production*, 2504.14303. 7, 8

[1004] G. Vasilev, G. Vankova and G. Bozhkova, *Optimization of singly-charged particles identification with the AMS02 RICH detector by a machine learning method*, *Astropart.Phys.* **171** (4, 2025) 103134, [2504.01265].

[1005] G. Bíró, G. Papp and G. G. Barnaföldi, *Estimating event-by-event multiplicity by a Machine Learning Method for Hadronization Studies*, vol. 40, p. 2542011, 8, 2024. 2408.17130. DOI.

[1006] P. Simkina, F. Couderc, J. Malclès and M. O. Sahin, *Reconstruction of electromagnetic showers in calorimeters using Deep Learning*, *Eur.Phys.J.C* **84** (11, 2023) 639, [2311.17914].

[1007] S. Dubey, T. E. Browder, S. Kohani, R. Mandal, A. Sibidanov and R. Sinha, *Training Deep 3D Convolutional Neural Networks to Extract BSM Physics Parameters Directly from HEP Data: a Proof-of-Concept Study Using Monte Carlo Simulations*, 2311.13060.

[1008] Z. Yang et al., *First attempt of directionality reconstruction for atmospheric neutrinos in a large homogeneous liquid scintillator detector*, *Phys.Rev.D* **109** (10, 2023) 052005, [2310.06281].

[1009] A. Schröder, L. van Velzen, M. Kelder and S. Schäfer, *Improving the temporal resolution of event-based electron detectors using neural network cluster analysis*, *Ultramicroscopy* **256** (7, 2023) 113881, [2307.16666].

[1010] I. A. Goos, X. Bertou and T. Pierog, *Determination of high-energy hadronic interaction properties from observables of proton initiated extensive air showers*, 2304.08007.

[1011] X. Meng, Y. Zhang, X. Zhang, S. Jin, T. Wang, L. Jiang et al., *Machine Learning Assisted Vector Atomic Magnetometry*, *Nature Commun.* **14** (12, 2022) 6105, [2301.05707].

[1012] N. Castro, K. Cranmer, A. V. Gritsan, J. Howarth, G. Magni, K. Mimasu et al., *LHC EFT WG Report: Experimental Measurements and Observables*, 2211.08353. 10

[1013] S. Craven, D. Croon, D. Cutting and R. Houtz, *Machine learning a manifold*, *Phys.Rev.D* **105** (12, 2021) 096030, [2112.07673].

[1014] J. Alda, J. Guasch and S. Penaranda, *Using Machine Learning techniques in phenomenological studies in flavour physics*, *JHEP* **07** (9, 2021) 115, [2109.07405].

[1015] D. Kim, K. Kong, K. T. Matchev, M. Park and P. Shyamsundar, *Deep-Learned Event Variables for Collider Phenomenology*, *Phys.Rev.D* **107** (5, 2021) L031904, [2105.10126].

[1016] M. Lazzarin, S. Alioli and S. Carrazza, *MCNNTUNES: tuning Shower Monte Carlo generators with machine learning*, 2010.02213.

[1017] S. Chen, A. Glioti, G. Panico and A. Wulzer, *Parametrized classifiers for optimal EFT sensitivity*, *JHEP* **05** (7, 2020) 247, [2007.10356].

[1018] Y.-K. Lei, C. Liu and Z. Chen, *Numerical analysis of neutrino physics within a high scale supersymmetry model via machine learning*, 2006.01495. 7

[1019] B. Kriesten, A. NieMiera, W. Good, T. J. Hobbs and H.-W. Lin, *Decoding the proton's gluonic density with lattice QCD-informed machine learning*, 2507.17810. 7, 8

[1020] M. N. Costantini, L. Mantani, J. M. Moore and M. Ubiali, *A linear PDF model for Bayesian inference*, 2507.16913.

[1021] A. R. Singireddy et al., *Generalized Parton Distributions from Symbolic Regression*, 2504.13289. 7

[1022] A. Barontini, M. N. Costantini, G. De Crescenzo, S. Forte and M. Ubiali, *Evaluating the faithfulness of PDF uncertainties in the presence of inconsistent data*, 2503.17447.

[1023] M. Soleymaninia, H. Khanpour, M. Azizi and H. Hashamipour, *Improved Constraints on Pion Fragmentation Functions from Simulated Electron-Ion Collider Data*, 2503.16053.

[1024] J. Cruz-Martinez, T. Hasenack, F. Hekhorn, G. Magni, E. R. Nocera, T. R. Rabemananjara et al., *NNPDFpol2.0: unbiased global determination of polarized PDFs and their uncertainties at next-to-next-to-leading order*, *JHEP* **07** (3, 2025) 168, [2503.11814].

[1025] MAP Collaboration, *A Neural-Network Extraction of Unpolarised Transverse-Momentum-Dependent Distributions*, *Phys.Rev.Lett.* **135** (2, 2025) 021904, [2502.04166].

[1026] T. A. Chowdhury, T. Izubuchi, M. Kamruzzaman, N. Karthik, T. Khan, T. Liu et al., *Polarized and unpolarized gluon PDFs: generative machine learning applications for lattice QCD matrix elements at short distance and large momentum*, *Phys.Rev.D* **111** (9, 2024) 074509, [2409.17234].

[1027] B. Kriesten, J. Gomprecht and T. J. Hobbs, *Explainable AI classification for parton density theory*, *JHEP* **11** (7, 2024) 007, [2407.03411]. 10

[1028] S. Liuti, *Extraction of Information from Polarized Deep Exclusive Scattering with Machine Learning*, 2406.09258.

[1029] M. Yan, T.-J. Hou, Z. Li, K. Mohan and C. P. Yuan, *A generalized statistical model for fits to parton distributions*, *Phys.Rev.D* **112** (6, 2024) 034008, [2406.01664].

[1030] A. Barontini, N. Laurenti and J. Rojo, *NNPDF4.0 aN^{3}LO PDFs with QED corrections*, in *31st International Workshop on Deep-Inelastic Scattering and Related Subjects*, 6, 2024. 2406.01779.

[1031] S. A. Ochoa-Oregon, D. F. Rentería-Estrada, R. J. Hernández-Pinto, G. F. R. Sborlini and P. Zurita, *Using analytic models to describe effective PDFs*, *Phys.Rev.D* **110** (4, 2024) 036019, [2404.15175].

[1032] M. Soleymaninia, H. Hashamipour, M. Salajegheh, H. Khanpour, H. Spiesberger and U.-G. Meißner, *Determination of K^0_S Fragmentation Functions including BESIII Measurements and using Neural Networks*, *Phys.Rev.D* **110** (4, 2024) 014019, [2404.07334].

[1033] MAP collaboration, V. Bertone, A. Chiefa and E. R. Nocera, *Helicity-dependent parton distribution functions at next-to-next-to-leading order accuracy from inclusive and semi-inclusive deep-inelastic scattering data*, *Phys.Lett.B* **865** (4, 2024) 139497, [2404.04712].

[1034] M. N. Costantini, E. Hammou, Z. Kassabov, M. Madigan, L. Mantani, M. Morales Alvarado et al., *SIMUnet: an open-source tool for simultaneous global *fits of EFT Wilson coefficients and PDFs*, *Eur.Phys.J.C* **84** (2, 2024) 805, [2402.03308].

[1035] J. P. Gombas, R. Schwienhorst, B. Dong and J. Fein, *Using Machine Learning to Improve PDF Uncertainties*, in *16th International Workshop on Top Quark Physics*, 1, 2024. 2401.13050.

[1036] P. Dall'Olio, F. De Soto, C. Mezrag, J. M. Morgado Chávez, H. Moutarde, J. Rodríguez-Quintero et al., *Unraveling generalized parton distributions through Lorentz symmetry and partial DGLAP knowledge*, *Phys. Rev. D* **109** (2024) 096013, [2401.12013].

[1037] NNPDF Collaboration, *Determination of the theory uncertainties from missing higher orders on NNLO parton distributions with percent accuracy*, *Eur.Phys.J.C* **84** (1, 2024) 517, [2401.10319].

[1038] NNPDF Collaboration, *Photons in the proton: implications for the LHC*, *Eur.Phys.J.C* **84** (1, 2024) 540, [2401.08749].

[1039] B. Kriesten and T. J. Hobbs, *Learning PDFs through Interpretable Latent Representations in Mellin Space*, *Phys.Rev.D* **111** (12, 2023) 014028, [2312.02278].

[1040] T. Rabemananjara, *Towards an integrated determination of proton, deuteron and nuclear PDFs*, in *30th International Workshop on Deep-Inelastic Scattering and Related Subjects*, 7, 2023. 2307.05967.

[1041] I. P. Fernando and D. Keller, *A Modern Global Extraction of the Sivers Function*, *Phys.Rev.D* **108** (4, 2023) 054007, [2304.14328]. 7

[1042] X.-Y. Wang and C. Dong, *Research on the distribution formula of QCD strong coupling constant in medium and high energy scale region based on symbolic regression algorithm*, *Chin.Phys.Lett.* **41** (4, 2023) 031201, [2304.07682]. 7

[1043] Z. Kassabov, M. Madigan, L. Mantani, J. Moore, M. M. Alvarado, J. Rojo et al., *The top quark legacy of the LHC Run II for PDF and SMEFT analyses*, *JHEP* **05** (3, 2023) 205, [2303.06159].

[1044] X.-Y. Wang, C. Dong and Q. Wang, *Determination of the distribution of strong coupling constant with machine learning*, 2303.07968. 7

[1045] A. Candido, A. Garcia, G. Magni, T. Rabemananjara, J. Rojo and R. Stegeman, *Neutrino Structure Functions from GeV to EeV Energies*, 2302.08527.

[1046] J. Gao, M. Gao, T. J. Hobbs, D. Liu and X. Shen, *Simultaneous CTEQ-TEA extraction of PDFs and SMEFT parameters from jet and $t\bar{t}$ data*, *JHEP* **05** (2023) 003, [2211.01094].

[1047] X. Gao, A. D. Hanlon, J. Holligan, N. Karthik, S. Mukherjee, P. Petreczky et al., *Unpolarized proton PDF at NNLO from lattice QCD with physical quark masses*, *Phys. Rev. D* **107** (2023) 074509, [2212.12569]. 7

[1048] S. Iranipour and M. Ubiali, *A new generation of simultaneous fits to LHC data using deep learning*, *JHEP* **05** (1, 2022) 032, [2201.07240].

[1049] R. A. Khalek, *Exploring the substructure of nucleons and nuclei with machine learning*, other thesis, 10, 2021.

[1050] R. D. Ball et al., *An open-source machine learning framework for global analyses of parton distributions*, *Eur.Phys.J.C* **81** (9, 2021) 958, [2109.02671].

[1051] R. D. Ball et al., *The Path to Proton Structure at One-Percent Accuracy*, *Eur.Phys.J.C* **82** (9, 2021) 428, [2109.02653].

[1052] S. Carrazza, J. Cruz-Martinez and T. R. Rabemananjara, *Compressing PDF sets using generative adversarial networks*, *Eur.Phys.J.C* **81** (4, 2021) 530, [2104.04535]. 8

[1053] J. Grigsby, B. Kriesten, J. Hoskins, S. Liuti, P. Alonzi and M. Burkardt, *Deep Learning Analysis of Deeply Virtual Exclusive Photoproduction*, *Phys.Rev.D* **104** (12, 2020) 016001, [2012.04801].

[1054] L. Del Debbio, T. Giani, J. Karpie, K. Orginos, A. Radyushkin and S. Zafeiropoulos, *Neural-network analysis of Parton Distribution Functions from Ioffe-time pseudodistributions*, 2010.03996. 7

[1055] K. Holland, A. Ipp, D. I. Müller and U. Wenger, *Machine-learned RG-improved gauge actions and classically perfect gradient flows*, 2504.15870. 7

[1056] M. Favoni, *Symmetry-preserving neural networks in lattice field theories*. PhD thesis, Vienna, Tech. U., 2025. 2506.12493. 10.34726/hss.2025.89161.

[1057] T. Blum, A. Conigli, L. Geyer, S. Kuberski, A. Segner and H. Wittig, *Machine-learning techniques as noise reduction strategies in lattice calculations of the muon $g-2$*, in *41st International Symposium on Lattice Field Theory*, vol. LATTICE2024, p. 270, 2, 2025. 2502.10237. DOI.

[1058] Q. Zhu, G. Aarts, W. Wang, K. Zhou and L. Wang, *Physics-Conditioned Diffusion Models for Lattice Gauge Theory*, 2502.05504. 8

[1059] K. Holland, A. Ipp, D. I. Müller and U. Wenger, *HMC and gradient flow with machine-learned classically perfect fixed-point actions*, in *41st International Symposium on Lattice Field Theory*, vol. LATTICE2024, p. 466, 2, 2025. 2502.03315. DOI.

[1060] S.-Y. Chen, G. Aarts and B. Lucini, *Exploring Generative Networks for Manifolds with Non-Trivial Topology*, in *41st International Symposium on Lattice Field Theory*, vol. LATTICE2024, p. 042, 2, 2025. 2502.02127. DOI. 8

[1061] Y. Nagai, H. Ohno and A. Tomiya, *CASK: A Gauge Covariant Transformer for Lattice Gauge Theory*, *PoS* **LATTICE2024** (2025) 030, [2501.16955].

[1062] G. Aarts, K. Fukushima, T. Hatsuda, A. Ipp, S. Shi, L. Wang et al., *Physics-driven learning for inverse problems in quantum chromodynamics*, 2501.05580. 10

[1063] O. Vega, A. Lytle, J. Shen and A. X. El-Khadra, *Using AI for Efficient Statistical Inference of Lattice Correlators Across Mass Parameters*, *PoS* **LATTICE2024** (2025) 420, [2412.21147].

[1064] M. Caselle, E. Cellini and A. Nada, *Stochastic normalizing flows for Effective String Theory*, *PoS* **LATTICE2024** (2025) 027, [2412.19109]. 8

[1065] G. Aarts, L. Wang and K. Zhou, *Diffusion models and stochastic quantisation in lattice field theory*, *PoS* **LATTICE2024** (2025) 037, [2412.13704]. 8

[1066] D. E. Habibi, G. Aarts, L. Wang and K. Zhou, *Diffusion models learn distributions generated by complex Langevin dynamics*, *PoS* **LATTICE2024** (2025) 039, [2412.01919]. 8

[1067] B. J. Choi, H. Ohno, T. Sumimoto and A. Tomiya, *Machine Learning Estimation on the trace of inverse Dirac operator using the Gradient Boosting Decision Tree Regression*, *PoS* **LATTICE2024** (2024) 033, [2411.18170].

[1068] W. Kou and X. Chen, *Machine Learning Insights into Quark-Antiquark Interactions: Probing Field Distributions and String Tension in QCD*, *Eur.Phys.J.C* **85** (11, 2024) 261, [2411.14902]. 9

[1069] Q. Zhu, G. Aarts, W. Wang, K. Zhou and L. Wang, *Diffusion models for lattice gauge field simulations*, in *38th conference on Neural Information Processing Systems*, 10, 2024. 2410.19602. 8

[1070] M. Gerdes, P. de Haan, R. Bondesan and M. C. N. Cheng, *Continuous normalizing flows for lattice gauge theories*, 2410.13161.

[1071] L. Wang, T. Doi, T. Hatsuda and Y. Lyu, *Building Hadron Potentials from Lattice QCD with Deep Neural Networks*, in *41st International Symposium on Lattice Field Theory*, vol. LATTICE2024, p. 076, 10, 2024. 2410.03082. DOI.

[1072] M. Rovira, A. Parreño and R. J. Perry, *A Variational Approach to Quantum Field Theory*, in *10th International Conference on Quarks and Nuclear Physics*, vol. QNP2024, p. 036, 9, 2024. 2409.17887. DOI. 7

[1073] L. Gao, *Estimation of the pseudoscalar glueball mass based on a modified Transformer*, 2408.13280.

[1074] O.-Y. Luo, X. Chen, F.-P. Li, X.-H. Li and K. Zhou, *Neural Network Modeling of Heavy-Quark Potential from Holography*, *Eur.Phys.J.C* **85** (8, 2024) 637, [2408.03784].

[1075] L. Gao, *Study of the mass of pseudoscalar glueball with a deep neural network*, 2407.12010.

[1076] D. Bachtis, *Disordered Lattice Glass ϕ^4 Quantum Field Theory*, 2407.06569.

[1077] F.-J. Jiang, *Berezinskii–Kosterlitz–Thouless transition of the two-dimensional XY model on the honeycomb lattice*, *PTEP* **2024** (6, 2024) 103A02, [2406.14812].

[1078] R.-G. Cai, S. He, L. Li and H.-A. Zeng, *QCD Phase Diagram at finite Magnetic Field and Chemical Potential: A Holographic Approach Using Machine Learning*, 2406.12772.

[1079] D. Bachtis, *Generating configurations of increasing lattice size with machine learning and the inverse renormalization group*, in *EuroPLEx Final Conference*, vol. EuroPLEx2023, p. 001, 5, 2024. 2405.16288. DOI.

[1080] A. Apte, A. Ashmore, C. Cordova and T.-C. Huang, *Deep learning lattice gauge theories*, *Phys.Rev.B* **110** (5, 2024) 165133, [2405.14830].

[1081] T. Xu, L. Wang, L. He, K. Zhou and Y. Jiang, *Building imaginary-time thermal filed theory with artificial neural networks*, *Chin.Phys.C* **48** (5, 2024) 103101, [2405.10493].

[1082] X. Chen and M. Huang, *Flavor dependent Critical endpoint from holographic QCD through machine learning*, *JHEP* **02** (5, 2024) 123, [2405.06179].

[1083] Y. Bai and T.-K. Chen, *Flow-based Nonperturbative Simulation of First-order Phase Transitions*, *JHEP* **10** (4, 2024) 198, [2404.18323]. 8

[1084] R. Abbott, M. S. Albergo, D. Boyda, D. C. Hackett, G. Kanwar, F. Romero-López et al., *Multiscale Normalizing Flows for Gauge Theories*, *PoS* **LATTICE2023** (2024) 035, [2404.10819]. 8

[1085] J. Finkenrath, *Fine grinding localized updates via gauge equivariant flows in the 2D Schwinger model*, *PoS* **LATTICE2023** (2024) 022, [2402.12176].

[1086] J. Kim, G. Pederiva and A. Shindler, *Machine learning mapping of lattice correlated data*, *Phys.Lett.B* **856** (2, 2024) 138894, [2402.07450].

[1087] J. Lin, D. Luo, X. Yao and P. E. Shanahan, *Real-time Dynamics of the Schwinger Model as an Open Quantum System with Neural Density Operators*, *JHEP* **06** (2, 2024) 211, [2402.06607]. 7

[1088] C. Bonanno, A. Nada and D. Vadacchino, *Mitigating topological freezing using out-of-equilibrium simulations*, *JHEP* **04** (2024) 126, [2402.06561].

[1089] M.-H. Chu, J.-H. Lai, W. Wang, J. Zhang and Q. Zhu, *Lattice simulation of $SU(2)$ dark glueball with machine learning*, *Chin.Phys.C* **48** (2, 2024) 083108, [2402.03959].

[1090] P. A. Boyle, *Advances in algorithms for solvers and gauge generation*, 2401.16620.

[1091] X. Chen and M. Huang, *Machine learning holographic black hole from lattice QCD equation of state*, *Phys. Rev. D* **109** (2024) L051902, [2401.06417].

[1092] G. Catumba, A. Ramos and B. Zaldivar, *The dependence of observables on action parameters*, *PoS* **LATTICE2023** (2024) 020, [2401.06456].

[1093] K. Holland, A. Ipp, D. I. Müller and U. Wenger, *Machine learning a fixed point action for SU(3) gauge theory with a gauge equivariant convolutional neural network*, *Phys.Rev.D* **110** (1, 2024) 074502, [2401.06481].

[1094] J. Goswami, D. A. Clarke, P. Dimopoulos, F. Di Renzo, C. Schmidt, S. Singh et al., *Exploring the Critical Points in QCD with Multi-Point Padé and Machine Learning Techniques in (2+1)-flavor QCD*, *EPJ Web Conf.* **296** (1, 2024) 06007, [2401.05651].

[1095] G. Kanwar, *Flow-based sampling for lattice field theories*, 1, 2024. 2401.01297. 8

[1096] S. Lawrence and Y. Yamauchi, *Mitigating a discrete sign problem with extreme learning machines*, 2312.12636.

[1097] S. Foreman, X.-Y. Jin and J. C. Osborn, *MLMC: Machine Learning Monte Carlo for Lattice Gauge Theory*, *PoS* **LATTICE2023** (12, 2023) 036, [2312.08936].

[1098] L. Gao, H. Ying and J. Zhang, *A study of topological quantities of lattice QCD by a modified DCGAN frame*, *Chin.Phys.C* **48** (12, 2023) 053111, [2312.03023].

[1099] K. Holland, A. Ipp, D. I. Müller and U. Wenger, *Fixed point actions from convolutional neural networks*, in *40th International Symposium on Lattice Field Theory*, vol. LATTICE2023, p. 038, 11, 2023. 2311.17816. DOI.

[1100] O. Soloveva, A. Palermo and E. Bratkovskaya, *Extraction of the microscopic properties of quasi-particles using deep neural networks*, *Phys.Rev.C* **110** (11, 2023) 034908, [2311.15984].

[1101] L. Gao, Z. Cheng, H. Ying and J. Zhang, *Study of topological quantities of lattice QCD by a modified Wasserstein generative adversarial network*, *Phys.Rev.D* **109** (11, 2023) 074509, [2311.10108].

[1102] L. Wang, G. Aarts and K. Zhou, *Generative Diffusion Models for Lattice Field Theory*, in *37th Conference on Neural Information Processing Systems*, 11, 2023. 2311.03578. 8

[1103] A. Tomiya and Y. Nagai, *Equivariant Transformer is all you need*, in *40th International Symposium on Lattice Field Theory*, vol. LATTICE2023, p. 001, 10, 2023. 2310.13222. DOI. 8

[1104] D. Albandea, L. Del Debbio, P. Hernández, R. Kenway, J. M. Rossney and

A. Ramos, *Learning Trivializing Flows in a ϕ^4 theory from coarser lattices*, in *40th International Symposium on Lattice Field Theory*, vol. LATTICE2023, p. 013, 10, 2023. 2310.03381. DOI. 8

[1105] C. Ermann, S. Baker and M. M. Anber, *Breaking Free with AI: The Deconfinement Transition*, 2309.07225.

[1106] K. Kashiwa, Y. Namekawa, A. Ohnishi and H. Takase, *Application of the path optimization method to a discrete spin system*, *Phys.Rev.D* **108** (9, 2023) 094504, [2309.06018].

[1107] W. Detmold, G. Kanwar, Y. Lin, P. E. Shanahan and M. L. Wagman, *Signal-to-noise improvement through neural network contour deformations for 3D $SU(2)$ lattice gauge theory*, vol. LATTICE2023, p. 043, 9, 2023. 2309.00600. DOI.

[1108] M. Caselle, E. Cellini and A. Nada, *Sampling the lattice Nambu-Goto string using Continuous Normalizing Flows*, *JHEP* **02** (7, 2023) 048, [2307.01107].

[1109] M. Buzzicotti, A. De Santis and N. Tantalo, *Teaching to extract spectral densities from lattice correlators to a broad audience of learning-machines*, *Eur.Phys.J.C* **84** (7, 2023) 32, [2307.00808].

[1110] M. J. Riberdy, H. Dutrieux, C. Mezrag and P. Sznajder, *Combining lattice QCD and phenomenological inputs on generalised parton distributions at moderate skewness*, *Eur.Phys.J.C* **84** (6, 2023) 201, [2306.01647].

[1111] A. Singha, D. Chakrabarti and V. Arora, *Sampling $U(1)$ gauge theory using a re-trainable conditional flow-based model*, *Phys.Rev.D* **108** (6, 2023) 7, [2306.00581]. 8

[1112] C. Lehner and T. Wettig, *Gauge-equivariant pooling layers for preconditioners in lattice QCD*, *Phys.Rev.D* **110** (4, 2023) 034517, [2304.10438]. 7

[1113] M. Narciso Ferreira, *Evidence of the Schwinger mechanism from lattice QCD*, in *16th International Conference on the Structure of Baryons*, vol. 64, p. 27, 4, 2023. 2304.07800. DOI.

[1114] J. Bender, P. Emonts and J. I. Cirac, *A variational Monte Carlo algorithm for lattice gauge theories with continuous gauge groups: a study of (2+1)-dimensional compact QED with dynamical fermions at finite density*, *Phys.Rev.Res.* **5** (4, 2023) 043128, [2304.05916].

[1115] D. P. R, *Locality-constrained autoregressive cum conditional normalizing flow for lattice field theory simulations*, 2304.01798. 8

[1116] R. J. Hudspith and D. Mohler, *Exotic Tetraquark states with two $\bar{b}$-quarks and $J^P = 0^+$ and $1^+ B_s$ states in a nonperturbatively-tuned Lattice NRQCD setup*, *Phys.Rev.D* **107** (3, 2023) 114510, [2303.17295].

[1117] J. Aronsson, D. I. Müller and D. Schuh, *Geometrical aspects of lattice gauge equivariant convolutional neural networks*, 2303.11448. 7

[1118] K. A. Nicoli, C. J. Anders, T. Hartung, K. Jansen, P. Kessel and S. Nakajima, *Detecting and Mitigating Mode-Collapse for Flow-based Sampling of Lattice Field Theories*, *Phys.Rev.D* **108** (2, 2023) 114501, [2302.14082]. 8

[1119] D. Albandea, L. Del Debbio, P. Hernández, R. Kenway, J. M. Rossney and A. Ramos, *Learning Trivializing Flows*, *Eur.Phys.J.C* **83** (2, 2023) 676, [2302.08408]. 8

[1120] C. Lehner and T. Wettig, *Gauge-equivariant neural networks as preconditioners in lattice QCD*, *Phys.Rev.D* **108** (2, 2023) 034503, [2302.05419]. 7

[1121] J.-H. Peng, Y.-H. Tseng and F.-J. Jiang, *Machine learning phases of an Abelian gauge theory*, *PTEP* **2023** (12, 2022) 073A03, [2212.14655].

[1122] S. Lawrence and Y. Yamauchi, *Deep Learning of Fermion Sign Fluctuations*, *Phys.Rev.D* **107** (12, 2022) 114505, [2212.14606].

[1123] A. C. Aguilar, F. De Soto, M. N. Ferreira, J. Papavassiliou, F. Pinto-Gómez, C. D. Roberts et al., *Schwinger mechanism for gluons from lattice QCD*, *Phys. Lett. B* **841** (2023) 137906, [2211.12594].

[1124] S. Bacchio, P. Kessel, S. Schaefer and L. Vaitl, *Learning trivializing gradient flows for lattice gauge theories*, *Phys. Rev. D* **107** (2023) L051504, [2212.08469]. 7

[1125] Z. Chen, D. Luo, K. Hu and B. K. Clark, *Simulating 2+1D Lattice Quantum Electrodynamics at Finite Density with Neural Flow Wavefunctions*, 2212.06835.

[1126] M. Favoni, A. Ipp and D. I. Müller, *Applications of Lattice Gauge Equivariant Neural Networks*, *EPJ Web Conf.* **274** (2022) 09001, [2212.00832]. 7

[1127] F. Karsch, A. Lahiri, M. Neumann and C. Schmidt, *A machine learning approach to the classification of phase transitions in many flavor QCD*, *PoS* **LATTICE2022** (2023) 027, [2211.16232].

[1128] J. Kim and W. Unger, *Error reduction using machine learning on Ising worm simulation*, *PoS* **LATTICE2022** (2023) 018, [2212.02365].

[1129] N. Sale, B. Lucini and J. Giansiracusa, *Persistent homology as a probe for center vortices and deconfinement in SU(2) lattice gauge theory*, *PoS* **LATTICE2022** (2023) 387, [2211.16273].

[1130] T. Khan, T. Liu and R. S. Sufian, *Gluon helicity distribution in the nucleon from lattice QCD and machine learning*, *Phys.Rev.D* **108** (11, 2022) 074502, [2211.15587].

[1131] D. Albandea, L. Del Debbio, P. Hernández, R. Kenway, J. M. Rossney and

A. Ramos Martinez, *Learning trivializing flows*, *PoS* **LATTICE2022** (2023) 001, [2211.12806]. 8

[1132] Z. Kang, J. Zhu and J. Guo, *Massive gauge theory with quasigluon for hot SU(N): Phase transition and thermodynamics*, *Phys. Rev. D* **107** (2023) 076005, [2211.09442].

[1133] F.-P. Li, H.-L. Lü, L.-G. Pang and G.-Y. Qin, *Deep-learning quasi-particle masses from QCD equation of state*, *Phys.Lett.B* **844** (11, 2022) 138088, [2211.07994].

[1134] S. Chen, O. Savchuk, S. Zheng, B. Chen, H. Stoecker, L. Wang et al., *Fourier-flow model generating Feynman paths*, *Phys. Rev. D* **107** (2023) 056001, [2211.03470]. 8

[1135] D. Luo, S. Yuan, J. Stokes and B. K. Clark, *Gauge Equivariant Neural Networks for 2+1D U(1) Gauge Theory Simulations in Hamiltonian Formulation*, 2211.03198.

[1136] S. Shi, L. Wang and K. Zhou, *Rethinking the ill-posedness of the spectral function reconstruction – why is it fundamentally hard and how Artificial Neural Networks can help*, *Comput.Phys.Commun.* **282** (1, 2022) 108547, [2201.02564]. 7

[1137] S. Bulusu, M. Favoni, A. Ipp, D. I. Müller and D. Schuh, *Equivariance and generalization in neural networks*, vol. 258, p. 09001, 12, 2021. 2112.12493. DOI. 7

[1138] S.-Y. Chen, H.-T. Ding, F.-Y. Liu, G. Papp and C.-B. Yang, *Machine learning Hadron Spectral Functions in Lattice QCD*, in *38th International Symposium on Lattice Field Theory*, vol. LATTICE2021, p. 148, 12, 2021. 2112.00460. DOI.

[1139] M. Favoni, A. Ipp, D. I. Müller and D. Schuh, *Lattice gauge symmetry in neural networks*, in *38th International Symposium on Lattice Field Theory*, vol. LATTICE2021, p. 185, 11, 2021. 2111.04389. DOI.

[1140] N. T. T. Nguyen, G. T. Kenyon and B. Yoon, *A regression algorithm for accelerated lattice QCD that exploits sparse inference on the D-Wave quantum annealer*, *Sci. Rep.* **10** (2020) 10915, [1911.06267].

[1141] R. Zhang, Z. Fan, R. Li, H.-W. Lin and B. Yoon, *Machine-learning prediction for quasiparton distribution function matrix elements*, *Phys. Rev. D* **101** (2020) 034516, [1909.10990].

[1142] B. Yoon, T. Bhattacharya and R. Gupta, *Machine Learning Estimators for Lattice QCD Observables*, *Phys. Rev. D* **100** (2019) 014504, [1807.05971].

[1143] D. C. Hackett, C.-C. Hsieh, M. S. Albergo, D. Boyda, J.-W. Chen, K.-F. Chen et al., *Flow-based sampling for multimodal distributions in lattice field theory*, 2107.00734. 8

[1144] S. Shi, K. Zhou, J. Zhao, S. Mukherjee and P. Zhuang, *Heavy Quark Potential in QGP: DNN meets LQCD*, *Phys.Rev.D* **105** (5, 2021) 014017, [2105.07862].

[1145] S. Bulusu, M. Favoni, A. Ipp, D. I. Müller and D. Schuh, *Generalization capabilities of translationally equivariant neural networks*, *Phys.Rev.D* **104** (3, 2021) 074504, [2103.14686].

[1146] M. Favoni, A. Ipp, D. I. Müller and D. Schuh, *Lattice gauge equivariant convolutional neural networks*, *Phys.Rev.Lett.* **128** (12, 2020) 3, [2012.12901]. 7

[1147] G. Kanwar, M. S. Albergo, D. Boyda, K. Cranmer, D. C. Hackett, S. Racanière et al., *Equivariant flow-based sampling for lattice gauge theory*, 2003.06413. 7, 8

[1148] Z. Ghalenovi, M. M. Sorkhi and A. H. Sovizi, *Quark Model Study of Doubly Heavy Ξ and Ω Baryons via Deep Neural Network and Hybrid Optimization*, *Mod.Phys.Lett.A* **40** (11, 2024) 2550061, [2411.13091]. 7

[1149] M. Wolf, L. O. Stietz, P. L. S. Connor, P. Schleper and S. Bein, *Fast Perfekt: Regression-based refinement of fast simulation*, *SciPost Phys.Core* **8** (10, 2024) 021, [2410.15992].

[1150] E. Hirst, *Calabi-Yau Links and Machine Learning*, vol. 02, p. 3, 1, 2024. 2401.11550. DOI.

[1151] H. Reyes-Gonzalez and R. Torre, *The NFLikelihood: an unsupervised DNNLikelihood from Normalizing Flows*, *SciPost Phys.Core* **7** (9, 2023) 048, [2309.09743]. 8

[1152] M. Lei, K. V. Tsang, S. Gasiorowski, C. Li, Y. Nashed, G. Petrillo et al., *Implicit Neural Representation as a Differentiable Surrogate for Photon Propagation in a Monolithic Neutrino Detector*, 2211.01505. 10

[1153] O. Kitouni, N. Nolte and M. Williams, *Robust and Provably Monotonic Networks*, in *35th Conference on Neural Information Processing Systems*, vol. 4, p. 035020, 11, 2021. 2112.00038. DOI.

[1154] L. Wang, S. Shi and K. Zhou, *Reconstructing spectral functions via automatic differentiation*, *Phys.Rev.D* **106** (11, 2021) L051502, [2111.14760].

[1155] I. Chahrour and J. D. Wells, *Function Approximation for High-Energy Physics: Comparing Machine Learning and Interpolation Methods*, *SciPost Phys.* **12** (11, 2021) 187, [2111.14788].

[1156] W. Haddadin, *Invariant polynomials and machine learning*, 2104.12733.

[1157] A. Coccaro, M. Pierini, L. Silvestrini and R. Torre, *The DNNLikelihood: enhancing likelihood distribution with Deep Learning*, *Eur. Phys. J. C* **80** (2020) 664, [1911.03305].

[1158] J. Y. Araz, J. C. Criado and M. Spannwosky, *Elvet – a neural network-based differential equation and variational problem solver*, 2103.14575. 7

[1159] J. Bendavid, D. Conde, M. Morales-Alvarado, V. Sanz and M. Ubiali, *Symbolic regression and precision LHC physics*, 2508.00989. 7

[1160] S. Vent, R. Winterhalder and T. Plehn, *How to Deep-Learn the Theory behind Quark-Gluon Tagging*, 2507.21214. 10

[1161] H. Bahl, E. Fuchs, M. Menen and T. Plehn, *$\mathcal{CP}$-Analyses with Symbolic Regression*, 2507.05858.

[1162] S. V. Chekanov and H. Kjellerstrand, *Discovering the underlying analytic structure within Standard Model constants using artificial intelligence*, 2507.00225.

[1163] W.-J. Zhang, Z. Zhang, J. Hu, B.-N. Lu, J.-Y. Pang and Q. Wang, *Machine Learning Unveils the power law of Finite-Volume Energy Shifts*, *Chin.Phys.Lett.* **42** (3, 2025) 070202, [2503.06496].

[1164] N. Makke and S. Chawla, *Inferring Interpretable Models of Fragmentation Functions using Symbolic Regression*, *Mach.Learn.Sci.Tech.* **6** (1, 2025) 025003, [2501.07123].

[1165] M. Morales-Alvarado, D. Conde, J. Bendavid, V. Sanz and M. Ubiali, *Symbolic regression for precision LHC physics*, in *38th conference on Neural Information Processing Systems*, 12, 2024. 2412.07839.

[1166] H. F. Tsoi, D. Rankin, C. Caillol, M. Cranmer, S. Dasu, J. Duarte et al., *SymbolFit: Automatic Parametric Modeling with Symbolic Regression*, *Comput.Softw.Big Sci.* **9** (11, 2024) 12, [2411.09851].

[1167] P. B. Cushman, M. C. Fritts, A. D. Chambers, A. Roy and T. Li, *Strategies for Machine Learning Applied to Noisy HEP Datasets: Modular Solid State Detectors from SuperCDMS*, 2404.10971. 7

[1168] Y. Lu, Y.-J. Wang, Y. Chen and J.-J. Wu, *Rediscovery of Numerical Luscher's Formula from the Neural Network*, 2210.02184.

[1169] Z. Zhang, R. Ma, J. Hu and Q. Wang, *Discover the GellMann-Okubo formula with machine learning*, *Chin.Phys.Lett.* **39** (8, 2022) 111201, [2208.03165].

[1170] A. Butter, T. Plehn and N. Soybelman, *Back to the Formula – LHC Edition*, *SciPost Phys.* **16** (9, 2021) 037, [2109.10414]. 7

[1171] A. Gavrikov, J. García Pardiñas and A. Garfagnini, *DINAMO: Dynamic and INterpretable Anomaly MOnitoring for Large-Scale Particle Physics Experiments*, 2501.19237. 7

[1172] A. Brinkerhoff et al., *Anomaly Detection for Automated Data Quality Monitoring in the CMS Detector*, 2501.13789. 9

[1173] S. AbdusSalam, S. Abel and M. Crispim Romão, *Symbolic Regression for Beyond the Standard Model Physics*, *Phys.Rev.D* **111** (5, 2024) 015022, [2405.18471].

[1174] P.-C. Li, X.-X. Bi, Z. Zhang, X.-B. Deng, C. Li, L.-W. Wang et al., *A versatile framework for attitude tuning of beamlines at advanced light sources*, 2411.01278.

[1175] T. Shutt et al., *GAMPix: a novel fine-grained, low-noise and ultra-low power pixelated charge readout for TPCs*, 2402.00902.

[1176] CMS ECAL collaboration, D. Abadjiev et al., *Autoencoder-based Anomaly Detection System for Online Data Quality Monitoring of the CMS Electromagnetic Calorimeter*, *Comput.Softw.Big Sci.* **8** (9, 2023) 11, [2309.10157]. 9

[1177] R. Das, L. Favaro, T. Heimel, C. Krause, T. Plehn and D. Shih, *How to Understand Limitations of Generative Networks*, *SciPost Phys.* **16** (5, 2023) 031, [2305.16774]. 9

[1178] CMS Collaboration, *Autoencoder-based Online Data Quality Monitoring for the CMS Electromagnetic Calorimeter*, in *21th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI meets Reality*, 8, 2023. 2308.16659.

[1179] Z. Chen, K. T. Wong, B. Seo, M. Huang, M. K. Parit, H. Zhen et al., *Magnetic field regression using artificial neural networks for cold atom experiments*, *Chin.Phys.B* **33** (5, 2023) 026701, [2305.18822].

[1180] B. Joshi, T. Li, B. Liang, R. Rusack and J. Sun, *Predicting the Future of the CMS Detector: Crystal Radiation Damage and Machine Learning at the LHC*, 2303.15291.

[1181] CMS Muon Collaboration, *Machine Learning based tool for CMS RPC currents quality monitoring*, *Nucl. Instrum. Meth. A* **1054** (2023) 168449, [2302.02764].

[1182] R. Matha, S. Barland and F. Gustave, *High-availability displacement sensing with multi-channel self mixing interferometry*, *Opt. Express* **31** (2023) 21911–21923, [2302.00065].

[1183] N. Mukund et al., *First demonstration of neural sensing and control in a kilometer-scale gravitational wave observatory*, *Phys.Rev.Applied* **20** (1, 2023) 064041, [2301.06221]. 7

[1184] CMS Collaboration, *Search for CP violation in events with top quarks and Z bosons at $\sqrt{s}$ = 13 and 13.6 TeV*, 2505.21206. 7, 11

[1185] V. Sanz, *Learning symmetries in datasets*, 2504.05174.

[1186] S. Nabat, A. Ghosh, E. Witkowski, G. Kasieczka and D. Whiteson, *Learning Broken Symmetries with Approximate Invariance*, *Phys.Rev.D* **111** (12, 2024) 072002, [2412.18773].

[1187] D. Maître, V. S. Ngairangbam and M. Spannowsky, *Optimal Equivariant Architectures from the Symmetries of Matrix-Element Likelihoods*, *Mach.Learn.Sci.Tech.* **6** (10, 2024) 015059, [2410.18553]. 10

[1188] Y. Hendi, M. Larfors and M. Walden, *Learning Group Invariant Calabi-Yau Metrics by Fundamental Domain Projections*, *Mach.Learn.Sci.Tech.* **6** (7, 2024) 015050, [2407.06914].

[1189] S. S. Cruz, M. Kolosova, G. Petrucciani, C. R. Álvarez and P. Vischia, *Equivariant neural networks for robust CP observables*, *Phys.Rev.D* **110** (5, 2024) 096023, [2405.13524].

[1190] J. Spinner, V. Bresó, P. de Haan, T. Plehn, J. Thaler and J. Brehmer, *Lorentz-Equivariant Geometric Algebra Transformers for High-Energy Physics*, 2405.14806. 8

[1191] A. Bhardwaj, P. Konar and V. S. Ngairangbam, *Foundations of automatic feature extraction at LHC–point clouds and graphs*, *Eur.Phys.J.ST* (4, 2024) , [2404.16207].

[1192] R. Sahu, *CapsLorentzNet: Integrating Physics Inspired Features with Graph Convolution*, *Phys.Rev.D* **111** (3, 2024) 036037, [2403.11826].

[1193] A. Bhardwaj, C. Englert, W. Naskar, V. S. Ngairangbam and M. Spannowsky, *Equivariant, Safe and Sensitive – Graph Networks for New Physics*, *JHEP* **07** (2, 2024) 245, [2402.12449].

[1194] S. Bressler, I. Savoray and Y. Zurgil, *Learning New Physics from Data – a Symmetrized Approach*, *Phys.Rev.D* **110** (1, 2024) 095004, [2401.09530].

[1195] Z.-F. Gu, Y.-K. Yan and S.-F. Wu, *Neural ODEs for holographic transport models without translation symmetry*, *Eur.Phys.J.C* **85** (1, 2024) 63, [2401.09946].

[1196] S. Bright-Thonney, B. Nachman and J. Thaler, *Safe but Incalculable: Energy-weighting is not all you need*, *Phys.Rev.D* **110** (11, 2023) 014029, [2311.07652].

[1197] R. T. Forestano, K. T. Matchev, K. Matcheva, A. Roman, E. B. Unlu and S. Verner, *Discovering Sparse Representations of Lie Groups with Machine Learning*, *Phys.Lett.B* **844** (2, 2023) 138086, [2302.05383].

[1198] E. Buhmann, G. Kasieczka and J. Thaler, *EPiC-GAN: Equivariant Point Cloud Generation for Particle Jets*, *SciPost Phys.* **15** (1, 2023) 130, [2301.08128]. 8

[1199] Z. Hao, R. Kansal, J. Duarte and N. Chernyavskaya, *Lorentz group equivariant autoencoders*, *Eur. Phys. J. C* **83** (2023) 485, [2212.07347]. 7

[1200] W. Kou, X. Lin, B. Guo and X. Chen, *Physics-Informed Neural Network Approach to Quark-Antiquark Color Flux Tube*, 2506.03513. 7

[1201] M. P. Bento, H. B. Câmara and J. F. Seabra, *Unraveling particle dark matter with Physics-Informed Neural Networks*, *Phys.Lett.B* **868** (2, 2025) 139690, [2502.17597]. 11

[1202] K. Hashimoto, K. Matsuo, M. Murata and G. Ogiwara, *Comparative Study of Neural Network Methods for Solving Topological Solitons*, 2411.14942. 11

[1203] R. C. Terin, *Physics-informed neural networks viewpoint for solving the Dyson-Schwinger equations of quantum electrodynamics*, 2411.02177.

[1204] M. Panahi, G. M. Porta, M. Riva and A. Guadagnini, *Modelling parametric uncertainty in PDEs models via Physics-Informed Neural Networks*, *Advances in Water Resources* **195** (8, 2024) 104870, [2408.04690]. 11

[1205] S. Mizera, *Scattering with Neural Operators*, *Phys.Rev.D* **108** (8, 2023) L101701, [2308.14789]. 7, 11

[1206] CMS Collaboration, *Search for top squarks in final states with many light-flavor jets and 0, 1, or 2 charged leptons in proton-proton collisions at $\sqrt{s}$ = 13 TeV*, 2506.08825. 7, 11

[1207] CMS Collaboration, *Machine learning method for enforcing variable independence in background estimation with LHC data: ABCDisCoTEC*, 2506.08826.

[1208] I. Oleksiyuk, S. Voloshynovskiy and T. Golling, *TRANSIT your events into a new mass: Fast background interpolation for weakly-supervised anomaly searches*, *JHEP* **07** (3, 2025) 177, [2503.04342]. 9

[1209] F. Rothen, S. Klein, M. Leigh and T. Golling, *Enhancing generalization in high energy physics using white-box adversarial attacks*, *Phys.Rev.D* **112** (11, 2024) 016004, [2411.09296].

[1210] M. Algren, J. A. Raine and T. Golling, *Decorrelation using Optimal Transport*, *Eur.Phys.J.C* **84** (7, 2023) 579, [2307.05187].

[1211] A. Rabusov, D. Greenwald and S. Paul, *Partial wave analysis of $\tau^- \to \pi^-\pi^+\pi^-\nu_\tau$ at Belle*, *PoS* **ICHEP2022** (2022) 1034, [2211.11696].

[1212] S. Klein and T. Golling, *Decorrelation with conditional normalizing flows*, 2211.02486.

[1213] V. Mikuni, B. Nachman and D. Shih, *Online-compatible Unsupervised Non-resonant Anomaly Detection*, *Phys.Rev.D* **105** (11, 2021) 055006, [2111.06417]. 9

[1214] M. J. Dolan and A. Ore, *Metalearning and data augmentation for mass-generalized jet taggers*, *Phys. Rev. D* **105** (2022) 094030, [2111.06047].

[1215] A. Ghosh and B. Nachman, *A Cautionary Tale of Decorrelating Theory Uncertainties*, *Eur.Phys.J.C* **82** (9, 2021) 46, [2109.08159].

[1216] O. Kitouni, B. Nachman, C. Weisser and M. Williams, *Enhancing searches for resonances with machine learning and moment decomposition*, *JHEP* **04** (10, 2020) 070, [2010.09745].

[1217] G. Kasieczka, B. Nachman, M. D. Schwartz and D. Shih, *ABCDisCo: Automating the ABCD Method with Machine Learning*, 2007.14400.

[1218] J. M. Clavijo, P. Glaysher and J. M. Katzy, *Adversarial domain adaptation to reduce sample bias of a high energy physics classifier*, *Mach.Learn.Sci.Tech.* **3** (2020) 015014, [2005.00568].

[1219] A. Rogozhnikov, A. Bukva, V. V. Gligorov, A. Ustyuzhanin and M. Williams, *New approaches for boosting to uniformity*, *JINST* **10** (2015) T03002, [1410.4140].

[1220] S. Wunsch, S. Jórger, R. Wolf and G. Quast, *Reducing the dependence of the neural network function to systematic uncertainties in the input space*, 1907.11674.

[1221] C. Englert, P. Galler, P. Harris and M. Spannowsky, *Machine Learning Uncertainties with Adversarial Neural Networks*, *Eur. Phys. J.* **C79** (2019) 4, [1807.08763]. 11

[1222] L.-G. Xia, *QBDT, a new boosting decision tree method with systematical uncertainties into training for High Energy Physics*, *Nucl. Instrum. Meth.* **A930** (2019) 15–26, [1810.08387].

[1223] G. Kasieczka and D. Shih, *DisCo Fever: Robust Networks Through Distance Correlation*, 2001.05310.

[1224] ATLAS Collaboration, *Performance of mass-decorrelated jet substructure observables for hadronic two-body decay tagging in ATLAS*, *ATL-PHYS-PUB-2018-014* (2018) .

[1225] L. Bradshaw, R. K. Mishra, A. Mitridate and B. Ostdiek, *Mass Agnostic Jet Taggers*, 1908.08959.

[1226] C. Shimmin, P. Sadowski, P. Baldi, E. Weik, D. Whiteson, E. Goul et al., *Decorrelated Jet Substructure Tagging using Adversarial Neural Networks*, 1703.03507.

[1227] J. Stevens and M. Williams, *uBoost: A boosting method for producing uniform selection efficiencies from multivariate classifiers*, *JINST* **8** (2013) P12013, [1305.7248].

[1228] I. Moult, B. Nachman and D. Neill, *Convolved Substructure: Analytically Decorrelating Jet Substructure Observables*, *JHEP* **05** (2018) 002, [1710.06859].

[1229] J. Dolen, P. Harris, S. Marzani, S. Rappoccio and N. Tran, *Thinking outside the ROCs: Designing Decorrelated Taggers (DDT) for jet substructure*, *JHEP* **05** (2016) 156, [1603.00027].

[1230] G. Louppe, M. Kagan and K. Cranmer, *Learning to Pivot with Adversarial Networks*, in *Advances in Neural Information Processing Systems* (I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan et al., eds.), vol. 30, Curran Associates, Inc., 2017. 1611.01046. 7, 11

[1231] K. Bhimani, J. Gruszko, M. Clark, J. Wilkerson and A. Li, *CycleGAN-Driven Transfer Learning for Electronics Response Emulation in High-Purity Germanium Detectors*, 2507.09106. 8

[1232] M. Malekhosseini, S. Rostami, A. R. Olamaei and K. Azizi, *Exploring fully-heavy tetraquarks through the CGAN framework: Mass and width*, *Nucl.Phys.B* **1018** (3, 2025) 116977, [2503.00993].

[1233] J. L. Bonilla, K. M. Graczyk, A. M. Ankowski, R. D. Banerjee, B. E. Kowal, H. Prasad et al., *Generative adversarial neural networks for simulating neutrino interactions*, *Phys.Rev.D* **112** (2, 2025) 013007, [2502.20244].

[1234] S. Rostami, M. Malekhosseini, M. R. Ezabadi and K. Azizi, *CGAN-Based Framework for Meson Mass and Width Prediction*, 2501.18562.

[1235] B. Käch, I. Melzer-Pellmann and D. Krücker, *Pay Attention To Mean Fields For Point Cloud Generation*, 2408.04997.

[1236] M. Wojnar, *Applying generative neural networks for fast simulations of the ALICE (CERN) experiment*, 2407.16704. 8

[1237] T. Dooney, L. Curier, D. Tan, M. Lopez, C. Van Den Broeck and S. Bromuri, *cDVGAN: One Flexible Model for Multi-class Gravitational Wave Signal and Glitch Generation*, *Phys.Rev.D* **110** (1, 2024) 022004, [2401.16356].

[1238] E. Simsek, B. Isildak, A. Dogru, R. Aydogan, A. B. Bayrak and S. Ertekin, *CALPAGAN: Calorimetry for Particles Using Generative Adversarial Networks*, *PTEP* **2024** (7, 2024) , [2401.02248].

[1239] J. Chan, X. Ju, A. Kania, B. Nachman, V. Sangli and A. Siodmok, *Integrating Particle Flavor into Deep Learning Models for Hadronization*, *Phys.Rev.D* **111** (12, 2023) 116015, [2312.08453].

[1240] M. A. W. Scham, D. Krücker and K. Borras, *DeepTreeGANv2: Iterative Pooling of Point Clouds*, 2312.00042.

[1241] M. A. W. Scham, D. Krücker, B. Käch and K. Borras, *DeepTreeGAN: Fast Generation of High Dimensional Point Clouds*, *EPJ Web Conf.* **295** (11, 2023) 09010, [2311.12616].

[1242] M. Faucci Giannelli and R. Zhang, *CaloShowerGAN, a Generative Adversarial Networks model for fast calorimeter shower simulation*, *Eur.Phys.J.Plus* **139** (9, 2023) 597, [2309.06515].

[1243] J. Erdmann, A. van der Graaf, F. Mausolf and O. Nackenhorst, *SR-GAN for SR-gamma: photon super resolution at collider experiments*, *Eur.Phys.J.C* **83** (8, 2023) 1001, [2308.09025].

[1244] M. Barbetti, *Lamarr: LHCb ultra-fast simulation based on machine learning models deployed within Gauss*, in *21th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI meets Reality*, 3, 2023. 2303.11428.

[1245] T. Alghamdi et al., *Toward a generative modeling analysis of CLAS exclusive* 2π *photoproduction*, *Phys.Rev.D* **108** (7, 2023) 094030, [2307.04450].

[1246] J. Dubiński, K. Deja, S. Wenzel, P. Rokita and T. Trzciński, *Machine Learning methods for simulating particle response in the Zero Degree Calorimeter at the ALICE experiment, CERN*, *AIP Conf.Proc.* **3061** (6, 2023) 040001, [2306.13606].

[1247] J. Chan, X. Ju, A. Kania, B. Nachman, V. Sangli and A. Siodmok, *Fitting a Deep Generative Hadronization Model*, *JHEP* **09** (5, 2023) 084, [2305.17169].

[1248] S. Diefenbacher, E. Eren, F. Gaede, G. Kasieczka, A. Korol, K. Krüger et al., *New Angles on Fast Calorimeter Shower Simulation*, *Mach.Learn.Sci.Tech.* **4** (3, 2023) 035044, [2303.18150].

[1249] EXO Collaboration, *Generative adversarial networks for scintillation signal simulation in EXO-200*, *JINST* **18** (2023) P06005, [2303.06311].

[1250] H. Hashemi, N. Hartmann, S. Sharifzadeh, J. Kahn and T. Kuhr, *Ultra-High-Resolution Detector Simulation with Intra-Event Aware GAN and Self-Supervised Relational Reasoning*, *Nature Commun.* **15** (3, 2023) 4916, [2303.08046].

[1251] X. Yue et al., *Ultrafast CMOS image sensors and data-enabled super-resolution for multimodal radiographic imaging and tomography*, *PoS* **Pixel2022** (2023) 041, [2301.11865].

[1252] LHCb collaboration, L. Anderlini, C. Chimpoesh, N. Kazeev and A. Shishigina, *Generative models uncertainty estimation*, in *20th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI Decoded - Towards Sustainable, Diverse, Performant and Effective Scientific Computing*, vol. 2438, p. 012088, 10, 2022. 2210.09767. DOI.

[1253] ATLAS Collaboration, *Deep generative models for fast photon shower simulation in ATLAS*, *Comput.Softw.Big Sci.* **8** (10, 2022) 7, [2210.06204].

[1254] A. Rogachev and F. Ratnikov, *GAN with an Auxiliary Regressor for the Fast Simulation of the Electromagnetic Calorimeter Response*, in *20th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI Decoded - Towards Sustainable, Diverse, Performant and Effective Scientific Computing*, vol. 2438, p. 012086, 7, 2022. 2207.06329. DOI.

[1255] F. Ratnikov, A. Maevskiy, A. Zinchenko, V. Riabov, A. Sukhorosov and

D. Evdokimov, *Generative Surrogates for Fast Simulation: TPC Case*, *Nucl.Instrum.Meth.A* **1047** (7, 2022) 167743, [2207.04340].

[1256] LHCb collaboration, L. Anderlini, M. Barbetti, D. Derkach, N. Kazeev, A. Maevskiy and S. Mokhnenko, *Towards Reliable Neural Generative Modeling of Detectors*, *J.Phys.Conf.Ser.* **2438** (4, 2022) 012130, [2204.09947].

[1257] A. Ghosh, X. Ju, B. Nachman and A. Siodmok, *Towards a Deep Learning Model for Hadronization*, *Phys.Rev.D* **106** (3, 2022) 096020, [2203.12660].

[1258] S. Bieringer, A. Butter, S. Diefenbacher, E. Eren, F. Gaede, D. Hundhausen et al., *Calomplification - The Power of Generative Calorimeter Models*, *JINST* **17** (2, 2022) P09028, [2202.07352].

[1259] E. Buhmann, S. Diefenbacher, E. Eren, F. Gaede, D. Hundhausen, G. Kasieczka et al., *Hadrons, Better, Faster, Stronger*, *Mach.Learn.Sci.Tech.* **3** (12, 2021) 025014, [2112.09709]. 8

[1260] K. Desai, B. Nachman and J. Thaler, *SymmetryGAN: Symmetry Discovery with Deep Learning*, *Phys.Rev.D* **105** (12, 2021) 096031, [2112.05722].

[1261] A. Chisholm, T. Neep, K. Nikolopoulos, R. Owen, E. Reynolds and J. Silva, *Non-Parametric Data-Driven Background Modelling using Conditional Probabilities*, *JHEP* **10** (12, 2021) 001, [2112.00650].

[1262] L. Anderlini, *Machine Learning for the LHCb Simulation*, 10, 2021. 2110.07925.

[1263] J. Li, C. Zhang and R. Zhang, *Polarization measurement for the dileptonic channel of W^+W^- scattering using generative adversarial network*, *Phys.Rev.D* **105** (9, 2021) 016005, [2109.09924].

[1264] W. Mu, A. I. Himmel and B. Ramson, *Photon detection probability prediction using one-dimensional generative neural network*, *Mach.Learn.Sci.Tech.* **3** (9, 2021) 015033, [2109.07277].

[1265] G. R. Khattak, S. Vallecorsa, F. Carminati and G. M. Khan, *Fast Simulation of a High Granularity Calorimeter by Generative Adversarial Networks*, *Eur.Phys.J.C* **82** (9, 2021) 386, [2109.07388].

[1266] S. Shirobokov, V. Belavin, M. Kagan, A. Ustyuzhanin and A. G. Baydin, *Black-Box Optimization with Local Generative Surrogates*, in *Advances in Neural Information Processing Systems* (H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan and H. Lin, eds.), vol. 33, pp. 14650–14662, Curran Associates, Inc., Feb, 2020. 2002.04632. 8, 10

[1267] R. Kansal, J. Duarte, H. Su, B. Orzari, T. Tomei, M. Pierini et al., *Particle Cloud Generation with Message Passing Generative Adversarial Networks*, 2106.11535.

[1268] R. Winterhalder, M. Bellagente and B. Nachman, *Latent Space Refinement for Deep Generative Models*, 2106.00792. 8

[1269] T. Lebese, B. Mellado and X. Ruan, *The use of Generative Adversarial Networks to characterise new physics in multi-lepton final states at the LHC*, 2105.14933.

[1270] F. Rehm, S. Vallecorsa, K. Borras and D. Krücker, *Physics Validation of Novel Convolutional 2D Architectures for Speeding Up High Energy Physics Simulations*, vol. 251, p. 03042, 5, 2021. 2105.08960. DOI.

[1271] F. Rehm, S. Vallecorsa, K. Borras and D. Krücker, *Validation of Deep Convolutional Generative Adversarial Networks for High Energy Physics Calorimeter Simulations*, 3, 2021. 2103.13698.

[1272] S. Choi and J. H. Lim, *A Data-driven Event Generator for Hadron Colliders using Wasserstein Generative Adversarial Network*, 2102.11524.

[1273] Y. S. Lai, D. Neill, M. Płoskoń and F. Ringer, *Explainable machine learning of the underlying physics of high-energy particle collisions*, *Phys.Lett.B* **829** (12, 2020) 137055, [2012.06582]. 8

[1274] A. Maevskiy, F. Ratnikov, A. Zinchenko and V. Riabov, *Simulating the time projection chamber responses at the MPD detector using generative adversarial networks*, *Eur. Phys. J. C* **81** (2021) 599, [2012.04595].

[1275] R. Kansal, J. Duarte, B. Orzari, T. Tomei, M. Pierini, M. Touranakou et al., *Graph Generative Adversarial Networks for Sparse Data Generation in High Energy Physics*, *34th Conference on Neural Information Processing Systems* (11, 2020) , [2012.00173].

[1276] A. Butter, S. Diefenbacher, G. Kasieczka, B. Nachman and T. Plehn, *GANplifying Event Samples*, *SciPost Phys.* **10** (2020) 139, [2008.06545].

[1277] S. Diefenbacher, E. Eren, G. Kasieczka, A. Korol, B. Nachman and D. Shih, *DCTRGAN: Improving the Precision of Generative Models with Reweighting*, *JINST* **15** (2020) P11004, [2009.03796]. 10

[1278] Y. Alanazi et al., *AI-based Monte Carlo event generator for electron-proton scattering*, *Phys.Rev.D* **106** (8, 2020) 096002, [2008.03151].

[1279] E. Buhmann, S. Diefenbacher, E. Eren, F. Gaede, G. Kasieczka, A. Korol et al., *Getting High: High Fidelity Simulation of High Granularity Calorimeters with High Speed*, *Comput.Softw.Big Sci.* **5** (2020) 13, [2005.05334].

[1280] K. Wang and J. Zhu, *A Novel Scenario in the Semi-constrained NMSSM*, *JHEP* **06** (2020) 078, [2002.05554].

[1281] S. Farrell, W. Bhimji, T. Kurth, M. Mustafa, D. Bard, Z. Lukic et al., *Next*

Generation Generative Neural Networks for HEP, *EPJ Web Conf.* **214** (2019) 09005.

[1282] L. de Oliveira, M. Paganini and B. Nachman, *Controlling Physical Attributes in GAN-Accelerated Simulation of Electromagnetic Calorimeters*, *J. Phys. Conf. Ser.* **1085** (2018) 042017, [1711.08813].

[1283] L. de Oliveira, M. Paganini and B. Nachman, *Tips and Tricks for Training GANs with Physics Constraints*, 2017.

[1284] J. M. Urban and J. M. Pawlowski, *Reducing Autocorrelation Times in Lattice Simulations with Generative Adversarial Networks*, 1811.03533.

[1285] M. Erdmann, J. Glombitza and T. Quast, *Precise simulation of electromagnetic calorimeter showers using a Wasserstein Generative Adversarial Network*, *Comput. Softw. Big Sci.* **3** (2019) 4, [1807.01954].

[1286] H. Erbin and S. Krippendorf, *GANs for generating EFT models*, 1809.02612.

[1287] D. Derkach, N. Kazeev, F. Ratnikov, A. Ustyuzhanin and A. Volokhova, *RICH 2018*, 1903.11788.

[1288] K. Deja, T. Trzcinski and L. Graczykowski, *Generative models for fast cluster simulations in the TPC for the ALICE experiment*, *Proceedings, 23rd International Conference on Computing in High Energy and Nuclear Physics (CHEP 2018): Sofia, Bulgaria, July 9-13, 2018; EPJ Web Conf.* **214** (2019) 06003.

[1289] M. Erdmann, L. Geiger, J. Glombitza and D. Schmidt, *Generating and refining particle detector simulations using the Wasserstein distance in adversarial networks*, *Comput. Softw. Big Sci.* **2** (2018) 4, [1802.03325].

[1290] P. Musella and F. Pandolfi, *Fast and Accurate Simulation of Particle Detectors Using Generative Adversarial Networks*, *Comput. Softw. Big Sci.* **2** (2018) 8, [1805.00850].

[1291] K. Datta, D. Kar and D. Roy, *Unfolding with Generative Adversarial Networks*, 1806.00433. 10

[1292] S. Vallecorsa, *Generative models for fast simulation*, *Proceedings, 18th International Workshop on Advanced Computing and Analysis Techniques in Physics Research (ACAT 2017): Seattle, WA, USA, August 21-25, 2017; J. Phys. Conf. Ser.* **1085** (2018) 022005.

[1293] F. Carminati, A. Gheata, G. Khattak, P. Mendez Lorenzo, S. Sharan and S. Vallecorsa, *Three dimensional Generative Adversarial Networks for fast simulation*, *Proceedings, 18th International Workshop on Advanced Computing and Analysis Techniques in Physics Research (ACAT 2017): Seattle, WA, USA, August 21-25, 2017; J. Phys. Conf. Ser.* **1085** (2018) 032016.

[1294] K. Zhou, G. Endrodi, L.-G. Pang and H. Stocker, *Regressive and generative neural networks for scalar field theory*, *Phys. Rev.* **D100** (2019) 011501, [1810.12879].

[1295] ATLAS Collaboration, *Deep generative models for fast shower simulation in ATLAS*, *ATL-SOFT-PUB-2018-001* (Jul, 2018) . 8

[1296] V. Chekalina, E. Orlova, F. Ratnikov, D. Ulyanov, A. Ustyuzhanin and E. Zakharov, *Generative Models for Fast Calorimeter Simulation.LHCb case*, *CHEP 2018* (2018) , [1812.01319].

[1297] B. Hashemi, N. Amin, K. Datta, D. Olivito and M. Pierini, *LHC analysis-specific datasets with Generative Adversarial Networks*, 1901.05282.

[1298] R. Di Sipio, M. Faucci Giannelli, S. Ketabchi Haghighat and S. Palazzo, *DijetGAN: A Generative-Adversarial Network Approach for the Simulation of QCD Dijet Events at the LHC*, 1903.02433.

[1299] J. Lin, W. Bhimji and B. Nachman, *Machine Learning Templates for QCD Factorization in the Search for Physics Beyond the Standard Model*, *JHEP* **05** (2019) 181, [1903.02556].

[1300] A. Butter, T. Plehn and R. Winterhalder, *How to GAN LHC Events*, *SciPost Phys.* **7** (2019) 075, [1907.03764].

[1301] S. Carrazza and F. A. Dreyer, *Lund jet images from generative and cycle-consistent adversarial networks*, *Eur. Phys. J.* **C79** (2019) 979, [1909.01359].

[1302] SHiP Collaboration, *Fast simulation of muons produced at the SHiP experiment using Generative Adversarial Networks*, 1909.04451.

[1303] S. Vallecorsa, F. Carminati and G. Khattak, *3D convolutional GAN for fast simulation*, *Proceedings, 23rd International Conference on Computing in High Energy and Nuclear Physics (CHEP 2018): Sofia, Bulgaria, July 9-13, 2018; EPJ Web Conf.* **214** (2019) 02010.

[1304] M. Bellagente, A. Butter, G. Kasieczka, T. Plehn and R. Winterhalder, *How to GAN away Detector Effects*, 1912.00477. 10

[1305] J. Arjona Martinez, T. Q. Nguyen, M. Pierini, M. Spiropulu and J.-R. Vlimant, *Particle Generative Adversarial Networks for full-event simulation at the LHC and their application to pileup description*, *ACAT 2019* (2019) , [1912.02748].

[1306] A. Butter, T. Plehn and R. Winterhalder, *How to GAN Event Subtraction*, 1912.08824.

[1307] S. Otten, S. Caron, W. de Swart, M. van Beekveld, L. Hendriks, C. van Leeuwen et al., *Event Generation and Statistical Sampling for Physics with Deep Generative Models and a Density Information Buffer*, *Nature Commun.* **12** (2021) 2985, [1901.00875]. 8

[1308] S. Alonso-Monsalve and L. H. Whitehead, *Image-based model parameter optimization using Model-Assisted Generative Adversarial Networks*, 1812.00879.

[1309] M. Paganini, L. de Oliveira and B. Nachman, *CaloGAN : Simulating 3D high energy particle showers in multilayer electromagnetic calorimeters with generative adversarial networks*, *Phys. Rev.* **D97** (2018) 014021, [1712.10321].

[1310] M. Paganini, L. de Oliveira and B. Nachman, *Accelerating Science with Generative Adversarial Networks: An Application to 3D Particle Showers in Multilayer Calorimeters*, *Phys. Rev. Lett.* **120** (2018) 042003, [1705.02355].

[1311] L. de Oliveira, M. Paganini and B. Nachman, *Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis*, 1701.05927. 8

[1312] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair et al., *Generative Adversarial Networks*, 1406.2661. 8

[1313] B. M. Dillon, J. Harkin and A. Javed, *Anomaly detection with spiking neural networks for LHC physics*, 2508.00063. 8, 9

[1314] S. Krippendorf and Z. Liu, *Solving inverse problems of Type IIB flux vacua with conditional generative models*, 2506.22551. 11

[1315] D. Smith, A. Ghosh, J. Liu, P. Baldi and D. Whiteson, *Fast multi-geometry calorimeter simulation with conditional self-attention variational autoencoders*, 2411.05996.

[1316] Q. Liu, C. Shimmin, X. Liu, E. Shlizerman, S. Li and S.-C. Hsu, *Calo-VQ: Vector-Quantized Two-Stage Generative Model in Calorimeter Simulation*, 2405.06605.

[1317] B. Hashemi, *Deep Generative Models for Ultra-High Granularity Particle Physics Detector Simulation: A Voyage From Emulation to Extrapolation*, other thesis, 3, 2024. 10.5282/edoc.34137.

[1318] Y.-T. Zhang, X.-T. Wang and J.-C. Yang, *Searching for gluon quartic gauge couplings at muon colliders using the auto-encoder*, *Phys.Rev.D* **109** (11, 2023) 095028, [2311.16627]. 9

[1319] S. V. Chekanov and R. Zhang, *Boosting sensitivity to new physics with unsupervised anomaly detection in dijet resonance search*, *Eur.Phys.J.Plus* **139** (8, 2023) 237, [2308.02671]. 9

[1320] L. Anzalone, S. S. Chhibra, B. Maier, N. Chernyavskaya and M. Pierini, *Triggering Dark Showers with Conditional Dual Auto-Encoders*, *Mach.Learn.Sci.Tech.* **5** (6, 2023) 035064, [2306.12955].

[1321] S. Roche, Q. Bayer, B. Carlson, W. Ouligian, P. Serhiayenka, J. Stelzer et al., *Nanosecond anomaly detection with decision trees for high energy physics and real-time application to exotic Higgs decays*, *Nature Commun.* **15** (4, 2023) 3527, [2304.03836]. 9

[1322] J. C. Cresswell, B. L. Ross, G. Loaiza-Ganem, H. Reyes-Gonzalez, M. Letizia and A. L. Caterini, *CaloMan: Fast generation of calorimeter showers with density estimation on learned manifolds*, in *36th Conference on Neural Information Processing Systems*, 11, 2022. 2211.15380. 8, 9

[1323] A. Abhishek, E. Drechsler, W. Fedorko and B. Stelzer, *CaloDVAE : Discrete Variational Autoencoders for Fast Calorimeter Shower Simulation*, 10, 2022. 2210.07430.

[1324] J. H. Collins, Y. Huang, S. Knapen, B. Nachman and D. Whiteson, *Machine-Learning Compression for Particle Physics Discoveries*, 2210.11489.

[1325] P. Ilten, T. Menzo, A. Youssef and J. Zupan, *Modeling hadronization using machine learning*, *SciPost Phys.* **14** (3, 2022) 027, [2203.04983].

[1326] M. Touranakou, N. Chernyavskaya, J. Duarte, D. Gunopulos, R. Kansal, B. Orzari et al., *Particle-based Fast Jet Simulation at the LHC with Variational Autoencoders*, *Mach.Learn.Sci.Tech.* **3** (3, 2022) 035003, [2203.00520].

[1327] P. Jawahar, T. Aarrestad, M. Pierini, K. A. Wozniak, J. Ngadiuba, J. Duarte et al., *Improving Variational Autoencoders for New Physics Detection at the LHC with Normalizing Flows*, *Front.Big Data* **5** (10, 2021) 803685, [2110.08508]. 8, 9

[1328] B. Orzari, T. Tomei, M. Pierini, M. Touranakou, J. Duarte, R. Kansal et al., *Sparse Data Generation for Particle-Based Simulation of Hadronic Jets in the LHC*, in *38th International Conference on Machine Learning Conference*, 9, 2021. 2109.15197.

[1329] J. H. Collins, *An Exploration of Learnt Representations of W Jets*, 9, 2021. 2109.10919. 10

[1330] C. Fanelli and J. Pomponi, *DeepRICH: Learning Deeply Cherenkov Detectors*, *Mach. Learn. Sci. Tech.* **1** (11, 2019) 015010, [1911.11717].

[1331] K. Deja, J. Dubiński, P. Nowak, S. Wenzel and T. Trzciński, *End-to-end sinkhorn autoencoder with noise generator*, 2020. 10.1109/ACCESS.2020.3048622.

[1332] B. Bortolato, B. M. Dillon, J. F. Kamenik and A. Smolkovič, *Bump Hunting in Latent Space*, *Phys.Rev.D* **105** (3, 2021) 115009, [2103.06595]. 9

[1333] E. Buhmann, S. Diefenbacher, E. Eren, F. Gaede, G. Kasieczka, A. Korol et al., *Decoding Photons: Physics in the Latent Space of a BIB-AE Generative Network*, *EPJ Web Conf.* **251** (2, 2021) 03003, [2102.12491].

[1334] K. Dohi, *Variational Autoencoders for Jet Simulation*, 2009.04842.

[1335] T. Cheng, J.-F. Arguin, J. Leissner-Martin, J. Pilette and T. Golling, *Variational Autoencoders for Anomalous Jet Tagging*, *Phys.Rev.D* **107** (7, 2020) 016002, [2007.01850]. 9

[1336] J. W. Monk, *Deep Learning as a Parton Shower*, *JHEP* **12** (2018) 021, [1807.03685]. 8

[1337] E. Bothmann, T. Janßen, M. Knobbe, B. Schmitzer and F. Sinz, *Efficient many-jet event generation with Flow Matching*, 2506.18987. 8, 9

[1338] V. S. Ngairangbam, M. Spannowsky and T. Sypchenko, *Improved Ground State Estimation in Quantum Field Theories via Normalising Flow-Assisted Neural Quantum States*, 2506.12128. 11

[1339] O. Amram and M. Szewc, *Data-Driven High-Dimensional Statistical Inference with Generative Models*, 2506.06438. 10

[1340] T. Janßen, R. Poncelet and S. Schumann, *Sampling NNLO QCD phase space with normalizing flows*, 2505.13608. 9

[1341] J. Giroux, M. Martinez and C. Fanelli, *Generative Models for Fast Simulation of Cherenkov Detectors at the Electron-Ion Collider*, 2504.19042. 8

[1342] E. Gendreau-Distler, L. L. Pottier and H. Wang, *Transforming Simulation to Data Without Pairing*, in *38th conference on Neural Information Processing Systems*, 4, 2025. 2504.12343. 10

[1343] J. Erdmann, J. Kann, F. Mausolf and P. Wissmann, *ParaFlow: fast calorimeter simulations parameterized in upstream material configurations*, *Eur.Phys.J.C* **85** (3, 2025) 857, [2503.21461].

[1344] E. Dreyer, E. Gross, D. Kobylianskii, V. Mikuni and B. Nachman, *Conditional Deep Generative Models for Simultaneous Simulation and Reconstruction of Entire Events*, 2503.19981. 8

[1345] J. Y. Araz, A. Beck, M. Reboud, M. Spannowsky and D. van Dyk, *Communicating Likelihoods with Normalising Flows*, 2502.09494. 10

[1346] R. Baruah, S. Mondal, S. K. Patra and S. Roy, *Normalizing Flow-Assisted Nested Sampling on Type-II Seesaw Model*, *Eur.Phys.J.C* **85** (1, 2025) 816, [2501.16432]. 9

[1347] A. Kofler, V. Stimper, M. Mikhasenko, M. Kagan and L. Heinrich, *Flow Annealed Importance Sampling Bootstrap meets Differentiable Particle Physics*, in *38th conference on Neural Information Processing Systems*, vol. 6, p. 025061, 11, 2024. 2411.16234. DOI. 9

[1348] M. Saito, M. Morinaga, T. Kishimoto and J. Tanaka, *Signal model parameter scan using Normalizing Flow*, *PoS* **ISGC2024** (9, 2024) 017, [2409.13201]. 10

[1349] N. Bodendorfer, O. Oktay, V. Gautam, M. Hanada and E. Rinaldi, *Variational Monte Carlo with Neural Network Quantum States for Yang-Mills Matrix Model*, *Phys.Rev.D* **112** (8, 2024) 046010, [2409.00398]. 11

[1350] T. Heimel, O. Mattelaer, T. Plehn and R. Winterhalder, *Differentiable MadNIS-Lite*, *SciPost Phys.* **18** (8, 2024) 017, [2408.01486]. 10

[1351] G. Quétant, J. A. Raine, M. Leigh, D. Sengupta and T. Golling, *PIPPIN: Generating variable length full events from partons*, *Phys.Rev.D* **110** (6, 2024) 076023, [2406.13074]. 8

[1352] E. Dreyer, E. Gross, D. Kobylianskii, V. Mikuni, B. Nachman and N. Soybelman, *Parnassus: An Automated Approach to Accurate, Precise, and Fast Detector Simulation and Reconstruction*, *Phys.Rev.Lett.* **133** (5, 2024) 211902, [2406.01620].

[1353] T. Buss, F. Gaede, G. Kasieczka, C. Krause and D. Shih, *Convolutional L2LFlows: Generating Accurate Showers in Highly Granular Calorimeters Using Convolutional Normalizing Flows*, *JINST* **19** (5, 2024) P09003, [2405.20407].

[1354] L. Favaro, A. Ore, S. P. Schweitzer and T. Plehn, *CaloDREAM – Detector Response Emulation via Attentive flow Matching*, *SciPost Phys.* **18** (5, 2024) 088, [2405.09629]. 8

[1355] H. Du, C. Krause, V. Mikuni, B. Nachman, I. Pang and D. Shih, *Unifying Simulation and Inference with Normalizing Flows*, *Phys.Rev.D* **111** (4, 2024) 076004, [2404.18992].

[1356] C. C. Daumann, M. Donega, J. Erdmann, M. Galli, J. L. Späh and D. Valsecchi, *One flow to correct them all: improving simulations in high-energy physics with a single normalising flow and a switch*, *Comput.Softw.Big Sci.* **8** (3, 2024) 15, [2403.18582].

[1357] S. Schnake, D. Krücker and K. Borras, *CaloPointFlow II Generating Calorimeter Showers as Point Clouds*, 2403.15782.

[1358] R. Kelleher and A. Vossen, *Normalizing Flows for Domain Adaptation when Identifying Λ Hyperon Events*, vol. 19, p. C06020, 3, 2024. 2403.14804. DOI. 10

[1359] F. Vaselli, F. Cattafesta, P. Asenov and A. Rizzi, *End-to-end simulation of particle physics events with Flow Matching and generator Oversampling*, *Mach.Learn.Sci.Tech.* **5** (2, 2024) 035007, [2402.13684]. 8

[1360] R. Kelleher, M. McEneaney and A. Vossen, *Improving Λ Signal Extraction with Domain Adaptation via Normalizing Flows*, in *25th International Spin Symposium*, vol. SPIN2023, p. 043, 3, 2024. 2403.14076. DOI. 10

[1361] N. Deutschmann and N. Götz, *Accelerating HEP simulations with Neural Importance Sampling*, *JHEP* **03** (2024) 083, [2401.09069]. 9

[1362] C. Krause, B. Nachman, I. Pang, D. Shih and Y. Zhu, *Anomaly detection with flow-based fast calorimeter simulators*, *Phys.Rev.D* **110** (12, 2023) 035036, [2312.11618]. 9

[1363] F. Ernst, L. Favaro, C. Krause, T. Plehn and D. Shih, *Normalizing Flows for High-Dimensional Detector Simulations*, *SciPost Phys.* **18** (12, 2023) 081, [2312.09290].

[1364] M. El Baz and F. Sánchez, *Fast Posterior Probability Sampling with Normalizing Flows and Its Applicability in Bayesian analysis in Particle Physics*, *Phys.Rev.D* **109** (12, 2023) 032008, [2312.02045].

[1365] C. Bierlich, P. Ilten, T. Menzo, S. Mrenna, M. Szewc, M. K. Wilkinson et al., *Towards a data-driven model of hadronization using normalizing flows*, *SciPost Phys.* **17** (11, 2023) 045, [2311.09296].

[1366] J. Gavranovič and B. P. Kerševan, *Systematic Evaluation of Generative Machine Learning Capability to Simulate Distributions of Observables at the Large Hadron Collider*, *Eur.Phys.J.C* **84** (10, 2023) 911, [2310.08994]. 9

[1367] T. M. Pham and X. Ju, *Simulation of Hadronic Interactions with Deep Generative Models*, in *26th International Conference on Computing in High Energy & Nuclear Physics*, vol. 295, p. 09034, 10, 2023. 2310.07553. DOI.

[1368] G. Bickendorf, M. Drees, G. Kasieczka, C. Krause and D. Shih, *Combining Resonant and Tail-based Anomaly Detection*, *Phys.Rev.D* **109** (9, 2023) 096031, [2309.12918]. 9

[1369] T. Golling, S. Klein, R. Mastandrea, B. Nachman and J. A. Raine, *Flows for Flows: Morphing one Dataset into another with Maximum Likelihood Estimation*, *Phys.Rev.D* **108** (9, 2023) 096018, [2309.06472].

[1370] I. Pang, J. A. Raine and D. Shih, *SuperCalo: Calorimeter shower super-resolution*, *Phys.Rev.D* **109** (8, 2023) 092009, [2308.11700].

[1371] M. R. Buckley, C. Krause, I. Pang and D. Shih, *Inductive CaloFlow*, *Phys.Rev.D* **109** (5, 2023) 033006, [2305.11934].

[1372] A. Xu, S. Han, X. Ju and H. Wang, *Generative Machine Learning for Detector Response Modeling with a Conditional Normalizing Flow*, *JINST* **19** (3, 2023) P02003, [2303.10148].

[1373] T. Golling, G. Kasieczka, C. Krause, R. Mastandrea, B. Nachman, J. A. Raine et al., *The Interplay of Machine Learning–based Resonant Anomaly Detection Methods*, *Eur.Phys.J.C* **84** (7, 2023) 241, [2307.11157]. 9

[1374] B. Nachman and R. Winterhalder, *ELSA - Enhanced latent spaces for improved collider simulations*, *Eur.Phys.J.C* **83** (5, 2023) 843, [2305.07696].

[1375] S. Diefenbacher, E. Eren, F. Gaede, G. Kasieczka, C. Krause, I. Shekhzadeh et al., *L2LFlows: Generating High-Fidelity 3D Calorimeter Images*, *JINST* **18** (2, 2023) P10017, [2302.11594].

[1376] T. Heimel, R. Winterhalder, A. Butter, J. Isaacson, C. Krause, F. Maltoni et al., *MadNIS – Neural Multi-Channel Importance Sampling*, *SciPost Phys.* **15** (12, 2022) 141, [2212.06172]. 9

[1377] M. Backes, A. Butter, M. Dunford and B. Malaescu, *An unfolding method based on conditional Invertible Neural Networks (cINN) using iterative training*, *SciPost Phys.Core* **7** (12, 2022) 007, [2212.08674]. 10

[1378] B. Käch, D. Krücker, I. Melzer-Pellmann, M. Scham, S. Schnake and A. Verney-Provatas, *JetFlow: Generating Jets with Conditioned and Mass Constrained Normalising Flows*, 2211.13630.

[1379] C. Krause, I. Pang and D. Shih, *CaloFlow for CaloChallenge Dataset 1*, *SciPost Phys.* **16** (10, 2022) 126, [2210.14245].

[1380] R. Verheyen, *Event Generation and Density Estimation with Surjective Normalizing Flows*, *SciPost Phys.* **13** (5, 2022) 047, [2205.01697]. 9

[1381] A. Butter, T. Heimel, S. Hummerich, T. Krebs, T. Plehn, A. Rousselot et al., *Generative Networks for Precision Enthusiasts*, *SciPost Phys.* **14** (10, 2021) 078, [2110.13632].

[1382] C. Krause and D. Shih, *CaloFlow II: Even Faster and Still Accurate Generation of Calorimeter Showers with Normalizing Flows*, *Phys.Rev.D* **107** (10, 2021) 113004, [2110.11377].

[1383] M. Vandegar, M. Kagan, A. Wehenkel and G. Louppe, *Neural Empirical Bayes: Source Distribution Estimation and its Applications to Simulation-Based Inference*, in *Proceedings of The 24th International Conference on Artificial Intelligence and Statistics* (A. Banerjee and K. Fukumizu, eds.), vol. 130 of *Proceedings of Machine Learning Research*, pp. 2107–2115, PMLR, 11, 2021. 2011.05836. 10

[1384] A. Hallin, J. Isaacson, G. Kasieczka, C. Krause, B. Nachman, T. Quadfasel et al., *Classifying Anomalies THrough Outer Density Estimation (CATHODE)*, *Phys.Rev.D* **106** (9, 2021) 055006, [2109.00546]. 9

[1385] S. B. Menary and D. D. Price, *Learning to discover: expressive Gaussian mixture models for multi-dimensional simulation and parameter inference in the physical sciences*, *Mach.Learn.Sci.Tech.* **3** (8, 2021) 015021, [2108.11481].

[1386] C. Krause and D. Shih, *CaloFlow: Fast and Accurate Generation of Calorimeter Showers with Normalizing Flows*, *Phys.Rev.D* **107** (6, 2021) 113003, [2106.05285]. 9

[1387] J. Hollingsworth, M. Ratz, P. Tanedo and D. Whiteson, *Efficient sampling of* *constrained high-dimensional theoretical spaces with machine learning*, *Eur.Phys.J.C* **81** (3, 2021) 1138, [2103.06957].

[1388] S. Bieringer, A. Butter, T. Heimel, S. Höche, U. Köthe, T. Plehn et al., *Measuring QCD Splittings with Invertible Networks*, *SciPost Phys.* **10** (12, 2020) 126, [2012.09873]. 10

[1389] Y. Lu, J. Collado, D. Whiteson and P. Baldi, *SARM: Sparse Autoregressive Model for Scalable Generation of Sparse Images in Particle Physics*, 2009.14017.

[1390] S. Choi, J. Lim and H. Oh, *Data-driven Estimation of Background Distribution through Neural Autoregressive Flows*, 2008.03636.

[1391] B. Nachman and D. Shih, *Anomaly Detection with Density Estimation*, *Phys. Rev. D* **101** (2020) 075042, [2001.04990]. 9

[1392] C. Gao, J. Isaacson and C. Krause, *i-flow: High-Dimensional Integration and Sampling with Normalizing Flows*, 2001.05486. 9

[1393] C. Gao, S. Höche, J. Isaacson, C. Krause and H. Schulz, *Event Generation with Normalizing Flows*, *Phys. Rev. D* **101** (2020) 076002, [2001.10028].

[1394] E. Bothmann, T. Janßen, M. Knobbe, T. Schmale and S. Schumann, *Exploring phase space with Neural Importance Sampling*, 2001.05478. 9

[1395] J. Brehmer and K. Cranmer, *Flows for simultaneous manifold learning and density estimation*, 2003.13913.

[1396] M. Bellagente, A. Butter, G. Kasieczka, T. Plehn, A. Rousselot and R. Winterhalder, *Invertible Networks or Partons to Detector and Back Again*, 2006.06685. 10

[1397] M. S. Albergo, G. Kanwar and P. E. Shanahan, *Flow-based generative models for Markov chain Monte Carlo in lattice field theory*, *Phys. Rev.* **D100** (2019) 034515, [1904.12072]. 8

[1398] D. Rezende and S. Mohamed, *Variational inference with normalizing flows*, *Proceedings of the 32nd International Conference on Machine Learning* **37** (07–09 Jul, 2015) 1530–1538. 8

[1399] V. D. Martinez, V. Manian and S. Malik, *Jet Image Generation in High Energy Physics Using Diffusion Models*, 2508.00250. 8

[1400] R. K. Barman, A. Choudhury and S. Sarkar, *Reconstructing Sparticle masses at the LHC using Generative Machine Learning*, 2507.20869. 8, 10

[1401] T. Buss, F. Gaede, G. Kasieczka, A. Korol, K. Krüger, P. McKeown et al., *CaloHadronic: a diffusion model for the generation of hadronic showers*, 2506.21720.

[1402] Y. Zhang, B.-H. Zhou, Q.-B. Liu, S. Li, S.-C. Hsu, T. Han et al., *Entanglement and Bell Nonlocality in $\tau^+\tau^-$ at the LHC using Machine Learning for Neutrino Reconstruction*, 2504.01496. 10

[1403] S. Nishimura, H. Otsuka and H. Uchiyama, *Diffusion-model approach to flavor models: A case study for S_4' modular flavor model*, 2504.00944. 10

[1404] S. Nishimura, H. Otsuka and H. Uchiyama, *Exploring the flavor structure of leptons via diffusion models*, 2503.21432.

[1405] MODE Collaboration, *End-to-End Detector Optimization with Diffusion models: A Case Study in Sampling Calorimeters*, *Particles* **8** (2, 2025) 47, [2502.02152]. 10

[1406] K. Fukushima and S. Kamata, *Stochastic quantization and diffusion models*, *J. Phys. Soc. Jap.* **94** (2025) 031010, [2411.11297]. 11

[1407] G. Aarts, D. E. Habibi, L. Wang and K. Zhou, *On learning higher-order cumulants in diffusion models*, in *38th conference on Neural Information Processing Systems*, vol. 6, p. 025004, 10, 2024. 2410.21212. DOI.

[1408] M. Kita, J. Dubiński, P. Rokita and K. Deja, *Generative Diffusion Models for Fast Simulations of Particle Collisions at CERN*, 2406.03233.

[1409] C. Jiang, S. Qian and H. Qu, *BUFF: Boosted Decision Tree based Ultra-Fast Flow matching*, 2404.18219.

[1410] D. Kobylianskii, N. Soybelman, E. Dreyer and E. Gross, *CaloGraph: Graph-based diffusion model for fast shower generation in calorimeters with irregular geometry*, *Phys.Rev.D* **110** (2, 2024) 072003, [2402.11575].

[1411] C. Jiang, S. Qian and H. Qu, *Choose Your Diffusion: Efficient and flexible ways to accelerate the diffusion model in fast high energy physics simulation*, *SciPost Phys.* **18** (1, 2024) 195, [2401.13162].

[1412] D. Sengupta, M. Leigh, J. A. Raine, S. Klein and T. Golling, *Improving new physics searches with diffusion models for event observables and jet constituents*, *JHEP* **04** (12, 2023) 109, [2312.10130]. 9

[1413] A. Butter, T. Jezo, M. Klasen, M. Kuschick, S. Palacios Schweitzer and T. Plehn, *Kicking it Off(-shell) with Direct Diffusion*, *SciPost Phys.Core* **7** (11, 2023) 064, [2311.17175].

[1414] P. Devlin, J.-W. Qiu, F. Ringer and N. Sato, *Diffusion model approach to simulating electron-proton scattering events*, *Phys.Rev.D* **110** (10, 2023) 016030, [2310.16308].

[1415] E. Buhmann, C. Ewen, G. Kasieczka, V. Mikuni, B. Nachman and D. Shih, *Full Phase Space Resonant Anomaly Detection*, *Phys.Rev.D* **109** (10, 2023) 055015, [2310.06897]. 9

[1416] E. Buhmann, F. Gaede, G. Kasieczka, A. Korol, W. Korcari, K. Krüger et al., *CaloClouds II: Ultra-Fast Geometry-Independent Highly-Granular Calorimeter Simulation*, *JINST* **19** (9, 2023) P04020, [2309.05704].

[1417] N. T. Hunt-Smith, W. Melnitchouk, F. Ringer, N. Sato, A. W. Thomas and M. J. White, *Accelerating Markov Chain Monte Carlo sampling with diffusion models*, *Comput.Phys.Commun.* **296** (9, 2023) 109059, [2309.01454].

[1418] V. Mikuni and B. Nachman, *CaloScore v2: Single-shot Calorimeter Shower Simulation with Diffusion Models*, *JINST* **19** (8, 2023) P02001, [2308.03847].

[1419] S. Diefenbacher, G.-H. Liu, V. Mikuni, B. Nachman and W. Nie, *Improving Generative Model-based Unfolding with Schrödinger Bridges*, *Phys.Rev.D* **109** (8, 2023) 076011, [2308.12351].

[1420] J. Cotler and S. Rezchikov, *Renormalizing Diffusion Models*, 2308.12355. 11

[1421] S. Diefenbacher, V. Mikuni and B. Nachman, *Refining Fast Calorimeter Simulations with a Schrödinger Bridge*, *JINST* **20** (8, 2023) P08007, [2308.12339].

[1422] O. Amram and K. Pedro, *CaloDiffusion with GLaM for High Fidelity Calorimeter Simulation*, *Phys.Rev.D* **108** (8, 2023) 072014, [2308.03876].

[1423] Z. Imani, S. Aeron and T. Wongjirad, *Score-based Diffusion Models for Generating Liquid Argon Time Projection Chamber Images*, *Phys.Rev.D* **109** (7, 2023) 072011, [2307.13687].

[1424] M. Leigh, D. Sengupta, J. A. Raine, G. Quétant and T. Golling, *PC-Droid: Faster diffusion and improved quality for particle cloud generation*, *Phys.Rev.D* **109** (7, 2023) 012010, [2307.06836].

[1425] F. T. Acosta, V. Mikuni, B. Nachman, M. Arratia, K. Barish, B. Karki et al., *Comparison of Point Cloud and Image-based Models for Calorimeter Fast Simulation*, *JINST* **19** (7, 2023) P05003, [2307.04780].

[1426] V. Mikuni and B. Nachman, *High-dimensional and Permutation Invariant Anomaly Detection*, *SciPost Phys.* **16** (6, 2023) 062, [2306.03933]. 9

[1427] A. Butter, N. Huetsch, S. P. Schweitzer, T. Plehn, P. Sorrenson and J. Spinner, *Jet Diffusion versus JetGPT – Modern Networks for the LHC*, *SciPost Phys.Core* **8** (5, 2023) 026, [2305.10475]. 8, 9

[1428] E. Buhmann, S. Diefenbacher, E. Eren, F. Gaede, G. Kasieczka, A. Korol et al., *CaloClouds: Fast Geometry-Independent Highly-Granular Calorimeter Simulation*, *JINST* **18** (5, 2023) P11025, [2305.04847].

[1429] A. Shmakov, K. Greif, M. Fenton, A. Ghosh, P. Baldi and D. Whiteson, *End-To-End Latent Variational Diffusion Models for Inverse Problems in High Energy Physics*, 2305.10399. 10

[1430] V. Mikuni, B. Nachman and M. Pettee, *Fast Point Cloud Generation with Diffusion Models in High Energy Physics*, *Phys.Rev.D* **108** (4, 2023) 036025, [2304.01266].

[1431] M. Leigh, D. Sengupta, G. Quétant, J. A. Raine, K. Zoch and T. Golling, *PC-JeDi: Diffusion for Particle Cloud Generation in High Energy Physics*, *SciPost Phys.* **16** (3, 2023) 018, [2303.05376].

[1432] V. Mikuni and B. Nachman, *Score-based Generative Models for Calorimeter Shower Simulation*, *Phys.Rev.D* **106** (6, 2022) 092009, [2206.11898]. 8

[1433] J. H. T. Yip, C. Arnal, F. Charton and G. Shiu, *Transforming Calabi-Yau Constructions: Generating New Calabi-Yau Manifolds with Transformers*, 2507.03732. 8, 11

[1434] A. Wang, A. Gandrakota, J. Ngadiuba, V. Sahu, P. Bhatnagar, E. E. Khoda et al., *Interpreting Transformers for Jet Tagging*, 12, 2024. 2412.03673. 11

[1435] W.-G. Paeng and D. Kwon, *Folded context condensation in Path Integral formalism for infinite context transformers*, 2405.04620.

[1436] A. Li, V. Krishnamohan, R. Kansal, R. Sen, S. Tsan, Z. Zhang et al., *Induced Generative Adversarial Particle Transformers*, in *37th Conference on Neural Information Processing Systems*, 12, 2023. 2312.04757. 8

[1437] E. Abasov, P. Volkov, G. Vorotnikov, L. Dudko, A. Zaborenko, E. Iudin et al., *Application of Kolmogorov-Arnold Networks in high energy physics*, *Moscow Univ.Phys.Bull.* **79** (9, 2024) S585, [2409.01724]. 8, 9

[1438] A. J. Larkoski, *Binary Discrimination Through Next-to-Leading Order*, *JHEP* **03** (9, 2023) 057, [2309.14417].

[1439] G. Barenboim, J. Hirn and V. Sanz, *Symmetry meets AI*, *SciPost Phys.* **11** (3, 2021) 014, [2103.06115].

[1440] M. Jercic and N. Poljak, *Exploring the Possibility of a Recovery of Physics Process Properties from a Neural Network Model*, 2007.13110.

[1441] A. Andreassen, I. Feige, C. Frye and M. D. Schwartz, *Binary JUNIPR: an interpretable probabilistic model for discrimination*, *Phys. Rev. Lett.* **123** (2019) 182001, [1906.10137].

[1442] A. Andreassen, I. Feige, C. Frye and M. D. Schwartz, *JUNIPR: a Framework for Unsupervised Machine Learning in Particle Physics*, *Eur.Phys.J.C* **79** (2018) 102, [1804.09720]. 8

[1443] L. Vermunt, Y. Seemann, A. Dubla, S. Floerchinger, E. Grossi, A. Kirchner et al., *Mapping QGP properties in Pb–Pb and Xe–Xe collisions at the LHC*, *Phys.Rev.C* **108** (8, 2023) 064908, [2308.16722]. 8

[1444] J. Liu, A. Ghosh, D. Smith, P. Baldi and D. Whiteson, *Geometry-aware Autoregressive Models for Calorimeter Shower Simulations*, in *36th Conference on Neural Information Processing Systems*, 12, 2022. 2212.08233.

[1445] M. Jia, K. Kumar, L. S. Mackey, A. Putra, C. Vilela, M. J. Wilking et al., *Maximum Likelihood Reconstruction of Water Cherenkov Events With Deep Generative Neural Networks*, *Front. Big Data* **5** (2022) 868333, [2202.01276].

[1446] C. Burton, S. Stubbs and P. Onyisi, *Mixture Density Network Estimation of Continuous Variable Maximum Likelihood Using Discrete Training Samples*, *Eur.Phys.J.C* **81** (3, 2021) 662, [2103.13416].

[1447] C. Chen, O. Cerri, T. Q. Nguyen, J.-R. Vlimant and M. Pierini, *Data Augmentation at the LHC through Analysis-specific Fast Simulation with Deep Learning*, 2010.01835. 8

[1448] W. Searle, C. Balázs, Y. Xiao and Y. Zhang, *Machine Learning Left-Right Breaking from Gravitational Waves*, 2506.09319. 9

[1449] F. A. de Souza, R. Boto, M. Crispim Romão, P. N. Figueiredo, J. C. Romão and J. a. P. Silva, *Unearthing large pseudoscalar Yukawa couplings with Machine Learning*, *JHEP* **07** (5, 2025) 268, [2505.10625].

[1450] H. Oh, *Training neural control variates using correlated configurations*, 2505.07719.

[1451] B. Nachman and D. Noll, *Stay Positive: Neural Refinement of Sample Weights*, 2505.03724. 10

[1452] M. A. Diaz, S. Dasmahapatra and S. Moretti, *hep-aid: A Python Library for Sample Efficient Parameter Scans in Beyond the Standard Model Phenomenology*, 2412.17675.

[1453] K. Ban, M. Park and R. Ramos, *LeStrat-Net: Lebesgue style stratification for Monte Carlo simulations powered by machine learning*, 2412.13982.

[1454] F. Calisto, R. Moodie and S. Zoia, *Learning Feynman integrals from differential equations with neural networks*, *JHEP* **07** (12, 2023) 124, [2312.02067].

[1455] J. Singh and T. Toll, *Predicting the Exclusive Diffractive Electron-Ion Cross Section at small x with Machine Learning in Sartre*, *Comput.Phys.Commun.* **292** (5, 2023) 108872, [2305.15880].

[1456] D. F. Renteria-Estrada, R. J. Hernandez-Pinto, G. F. R. Sborlini and P. Zurita, *Precision studies for the partonic kinematics calculation through Machine Learning*, vol. 4, p. 021134, 5, 2023. 2305.11369. DOI.

[1457] R. Jinno, G. Kälin, Z. Liu and H. Rubira, *Machine Learning Post-Minkowskian Integrals*, *JHEP* **07** (9, 2022) 181, [2209.01091].

[1458] D. Maître and R. Santos-Mateos, *Multi-variable Integration with a Neural Network*, *JHEP* **03** (11, 2022) 221, [2211.02834].

[1459] B. Yoon, *A machine learning approach for efficient multi-dimensional integration*, *Sci. Rep.* **11** (2021) 18965, [2009.06697].

[1460] M. Backes, A. Butter, T. Plehn and R. Winterhalder, *How to GAN Event Unweighting*, *SciPost Phys.* **10** (12, 2020) 089, [2012.07873].

[1461] R. Verheyen and B. Stienen, *Phase Space Sampling and Inference from Weighted Events with Autoregressive Flows*, 2011.13445.

[1462] I.-K. Chen, M. D. Klimek and M. Perelstein, *Improved Neural Network Monte Carlo Simulation*, 2009.07819.

[1463] B. Nachman and J. Thaler, *A Neural Resampler for Monte Carlo Reweighting with Preserved Uncertainties*, 2007.11586.

[1464] S. Carrazza and J. M. Cruz-Martinez, *VegasFlow: accelerating Monte Carlo simulation across multiple hardware platforms*, 2002.12921.

[1465] M. D. Klimek and M. Perelstein, *Neural Network-Based Approach to Phase Space Integration*, 1810.11509.

[1466] J. Bendavid, *Efficient Monte Carlo Integration Using Boosted Decision Trees and Generative Deep Neural Networks*, 1707.00028. 9

[1467] E. Cisbani et al., *AI-optimized detector design for the future Electron-Ion Collider: the dual-radiator RICH case*, *JINST* **15** (2020) P05009, [1911.05797]. 9

[1468] M. Frate, K. Cranmer, S. Kalia, A. Vandenberg-Rodes and D. Whiteson, *Modeling Smooth Backgrounds and Generic Localized Signals with Gaussian Processes*, 1709.05681. 9

[1469] S. Grossi, M. Letizia and R. Torre, *Comparing Generative Models with the New Physics Learning Machine*, 2508.02275. 9, 11

[1470] S. Grossi, M. Letizia and R. Torre, *Refereeing the referees: evaluating two-sample tests for validating generators in precision sciences*, *Mach. Learn. Sci. Tech.* **6** (2025) 015052, [2409.16336].

[1471] R. Kansal, A. Li, J. Duarte, N. Chernyavskaya, M. Pierini, B. Orzari et al., *Evaluating generative models in high energy physics*, *Phys. Rev. D* **107** (2023) 076017, [2211.10295]. 9

[1472] E. P. Santos, R. S. Pugina, E. G. Hilário, A. J. A. Carvalho, C. Jacinto, F. A. M. G. Rego-Filho et al., *Towards accurate real-time luminescence thermometry: an automated machine learning approach*, 2307.05497.

[1473] B. Kronheim, A. A. Kadhim, M. P. Kuchera, H. B. Prosper and R. Ramanujan, *Implicit Quantile Networks For Emulation in Jet Physics*, *Mach.Learn.Sci.Tech.* **5** (6, 2023) 045073, [2306.15053].

[1474] A. Li, J. Gruszko, B. Bos, T. Caldwell, E. León and J. Wilkerson, *Ad-hoc Pulse Shape Simulation using Cyclic Positional U-Net*, in *36th Conference on Neural Information Processing Systems*, 12, 2022. 2212.04950.

[1475] F. A. Di Bello, E. Dreyer, S. Ganguly, E. Gross, L. Heinrich, M. Kado et al., *Conditional Generative Modelling of Reconstructed Particles at Collider Experiments*, *Mach.Learn.Sci.Tech.* **4** (11, 2022) 045036, [2211.06406]. 9

[1476] E. Puljak, M. Pierini and A. Garcia-Saez, *Tensor Network for Anomaly Detection in the Latent Space of Proton Collision Events at the LHC*, 2506.00102. 9

[1477] C. L. Cheng, R. Das, R. Li, R. Mastandrea, V. Mikuni, B. Nachman et al., *Generator Based Inference (GBI)*, 2506.00119. 10

[1478] F. A. de Souza, M. Barros, N. F. Castro, M. Crispim Romão, C. Neiva and R. Pedro, *Sensitivity to New Physics Phenomena in Anomaly Detection: A Study of Untunable Hyperparameters*, 2505.13228.

[1479] ATLAS Collaboration, *Search for new physics in final states with semi-visible jets or anomalous signatures using the ATLAS detector*, *Phys.Rev.D* **112** (5, 2025) 012021, [2505.01634]. 11

[1480] L. Brennan, T. A. Vami, O. Amram, S. Sekhar, Y. Takahashi, L. Moureaux et al., *Weakly supervised anomaly detection with event-level variables*, 2504.13249.

[1481] S. V. Chekanov, W. Islam and N. Luongo, *Enhancing Sensitivity for Di-Higgs Boson Searches Using Anomaly Detection and Supervised Machine Learning Techniques*, 2504.12418.

[1482] A. Banda, C. K. Khosa and V. Sanz, *Strengthening Anomaly Awareness*, 2504.11520.

[1483] K.-X. Chen, Y.-C. Guo and J.-C. Yang, *Search for anomalous quartic gauge couplings in the process $\mu^+\mu^- \to \bar{\nu}\nu\gamma\gamma$ with a nested local outlier factor*, 2504.03145.

[1484] S. Klein, M. Leigh, S. Mulligan and T. Golling, *Strong CWoLa: Binary Classification Without Background Simulation*, 2503.14876.

[1485] K. Metzger, L. Xu, M. Sodini, T. K. Arrestad, K. Govorkova, G. Grosso et al., *Anomaly preserving contrastive neural embeddings for end-to-end model-independent searches at the LHC*, 2502.15926.

[1486] R. Gambhir, R. Mastandrea, B. Nachman and J. Thaler, *Isolating Unisolated*

Upsilons with Anomaly Detection in CMS Open Data, *Phys.Rev.Lett.* **135** (2, 2025) 021902, [2502.14036].

[1487] ATLAS Collaboration, *Weakly supervised anomaly detection for resonant new physics in the dijet final state using proton-proton collisions at $\sqrt{s} = 13$ TeV with the ATLAS detector*, 2502.09770. 11

[1488] A. Khot, X. Wang, A. Roy, V. Kindratenko and M. S. Neubauer, *Evidential Deep Learning for Uncertainty Quantification and Out-of-Distribution Detection in Jet Identification using Deep Neural Networks*, *Mach.Learn.Sci.Tech.* **6** (1, 2025) 035003, [2501.05656]. 11

[1489] J.-F. Arguin et al., *Automatizing the search for mass resonances using BumpNet*, *JHEP* **02** (1, 2025) 122, [2501.05603].

[1490] CMS Collaboration, *Model-agnostic search for dijet resonances with anomalous jet substructure in proton-proton collisions at $\sqrt{s}$ = 13 TeV*, *Rept.Prog.Phys.* **88** (12, 2024) 067802, [2412.03747].

[1491] R. Das and D. Shih, *SIGMA: Single Interpolated Generative Model for Anomalies*, 2410.20537.

[1492] DARWIN Collaboration, *Model-independent searches of new physics in DARWIN with a semi-supervised deep learning pipeline*, 2410.00755.

[1493] S. V. Chekanov, W. Islam, R. Zhang and N. Luongo, *ADFilter – A Web Tool for New Physics Searches With Autoencoder-Based Anomaly Detection Using Deep Unsupervised Neural Networks*, *Information* **16** (9, 2024) 258, [2409.03065].

[1494] G. Matos, E. Busch, K. R. Park and J. Gonski, *Semi-supervised permutation invariant particle-level anomaly detection*, *JHEP* **05** (8, 2024) 116, [2408.17409].

[1495] S. Caron, J. E. García Navarro, M. Moreno Llácer, P. Moskvitina, M. Rovers, A. Rubio Jímenez et al., *Universal anomaly detection at the LHC: transforming optimal classifiers and the DDD method*, *Eur. Phys. J. C* **85** (2025) 415, [2406.18469].

[1496] CMS Collaboration, *Anomaly Detection Based on Machine Learning for the CMS Electromagnetic Calorimeter Online Data Quality Monitoring*, in *20th International Conference on Calorimetry in Particle Physics*, vol. 320, p. 00048, 7, 2024. 2407.20278. DOI.

[1497] M. Leigh, D. Sengupta, B. Nachman and T. Golling, *Accelerating template generation in resonant anomaly detection searches with optimal transport*, 2407.19818.

[1498] G. Grosso, *Anomaly-aware summary statistic from data batches*, *JHEP* **12** (7, 2024) 093, [2407.01249].

[1499] C. Li et al., *Accelerating Resonance Searches via Signature-Oriented Pre-training*, 2405.12972.

[1500] C. L. Cheng, G. Singh and B. Nachman, *Incorporating Physical Priors into Weakly-Supervised Anomaly Detection*, *Phys.Rev.Lett.* **135** (5, 2024) 021801, [2405.08889].

[1501] I. Oleksiyuk, J. A. Raine, M. Krämer, S. Voloshynovskiy and T. Golling, *Cluster Scanning: a novel approach to resonance searches*, *JHEP* **06** (2024) 163, [2402.17714].

[1502] E. M. Metodiev, J. Thaler and R. Wynne, *Anomaly Detection in Collider Physics via Factorized Observables*, *Phys.Rev.D* **110** (11, 2023) 055012, [2312.00119].

[1503] R. Liu, A. Gandrakota, J. Ngadiuba, M. Spiropulu and J.-R. Vlimant, *Fast Particle-based Anomaly Detection Algorithm with Variational Autoencoder*, in *37th Conference on Neural Information Processing Systems*, 11, 2023. 2311.17162.

[1504] K. Bai, R. Mastandrea and B. Nachman, *Non-resonant Anomaly Detection with Background Extrapolation*, *JHEP* **04** (11, 2023) 059, [2311.12924].

[1505] M. Freytsis, M. Perelstein and Y. C. San, *Anomaly Detection in Presence of Irrelevant Features*, *JHEP* **02** (10, 2023) 220, [2310.13057].

[1506] ATLAS Collaboration, *Anomaly detection search for new resonances decaying into a Higgs boson and a generic new particle X in hadronic final states using $\sqrt{s} = 13$ TeV pp collisions with the ATLAS detector*, *Phys.Rev.D* **108** (6, 2023) 052009, [2306.03637].

[1507] L. Vaslin, V. Barra and J. Donini, *GAN-AE : An anomaly detection algorithm for New Physics search in LHC data*, *Eur.Phys.J.C* **83** (5, 2023) 1008, [2305.15179].

[1508] D. Sengupta, S. Klein, J. A. Raine and T. Golling, *CURTAINs Flows For Flows: Constructing Unobserved Regions with Maximum Likelihood Estimation*, *SciPost Phys.* **17** (5, 2023) 046, [2305.04646].

[1509] T. Golling et al., *The Mass-ive Issue: Anomaly Detection in Jet Physics*, in *34th Conference on Neural Information Processing Systems*, 3, 2023. 2303.14134.

[1510] R. Mastandrea and B. Nachman, *Efficiently Moving Instead of Reweighting Collider Events with Machine Learning*, in *36th Conference on Neural Information Processing Systems*, 12, 2022. 2212.06155.

[1511] G. Kasieczka, R. Mastandrea, V. Mikuni, B. Nachman, M. Pettee and D. Shih, *Anomaly Detection under Coordinate Transformations*, *Phys.Rev.D* **107** (9, 2022) 015009, [2209.06225].

[1512] A. Hallin, G. Kasieczka, T. Quadfasel, D. Shih and M. Sommerhalder, *Resonant* *anomaly detection without background sculpting*, *Phys.Rev.D* **107** (10, 2022) 114012, [2210.14924].

[1513] J. F. Kamenik and M. Szewc, *Null Hypothesis Test for Anomaly Detection*, *Phys.Lett.B* **840** (10, 2022) 137836, [2210.02226].

[1514] S. E. Park, P. Harris and B. Ostdiek, *Neural Embedding: Learning the Embedding of the Manifold of Physics Data*, *JHEP* **07** (8, 2022) 108, [2208.05484].

[1515] S. Caron, R. R. de Austri and Z. Zhang, *Mixture-of-theories Training: Can We Find New Physics and Anomalies Better by Mixing Physical Theories?*, *JHEP* **03** (7, 2022) 004, [2207.07631].

[1516] B. M. Dillon, L. Favaro, T. Plehn, P. Sorrenson and M. Krämer, *A Normalized Autoencoder for LHC Triggers*, *SciPost Phys.Core* **6** (6, 2022) 074, [2206.14225].

[1517] C. Fanelli, J. Giroux and Z. Papandreou, *"Flux+Mutability": A Conditional Generative Approach to One-Class Classification and Anomaly Detection*, *Mach.Learn.Sci.Tech.* **3** (4, 2022) 045012, [2204.08609].

[1518] M. Letizia, G. Losapio, M. Rando, G. Grosso, A. Wulzer, M. Pierini et al., *Learning new physics efficiently with nonparametric methods*, *Eur.Phys.J.C* **82** (4, 2022) 879, [2204.02317].

[1519] J. A. Raine, S. Klein, D. Sengupta and T. Golling, *CURTAINs for your Sliding Window: Constructing Unobserved Regions by Transforming Adjacent Intervals*, *Front.Big Data* **6** (3, 2022) 899345, [2203.09470].

[1520] M. Birman, B. Nachman, R. Sebbah, G. Sela, O. Turetz and S. Bressler, *Data-directed search for new physics based on symmetries of the SM*, *Eur. Phys. J. C* **82** (2022) 508, [2203.07529].

[1521] B. M. Dillon, R. Mastandrea and B. Nachman, *Self-supervised Anomaly Detection for New Physics*, *Phys.Rev.D* **106** (5, 2022) 056005, [2205.10380].

[1522] X.-H. Jiang, A. Juste, Y.-Y. Li and T. Liu, *Detecting new physics as novelty — Complementarity matters*, *JHEP* **10** (2022) 085, [2202.02165].

[1523] T. Buss, B. M. Dillon, T. Finke, M. Krämer, A. Morandini, A. Mück et al., *What's Anomalous in LHC Jets?*, *SciPost Phys.* **15** (2, 2022) 168, [2202.00686].

[1524] J. A. Aguilar-Saavedra, *Taming modeling uncertainties with Mass Unspecific Supervised Tagging*, *Eur.Phys.J.C* **82** (1, 2022) 270, [2201.11143].

[1525] L. Bradshaw, S. Chang and B. Ostdiek, *Creating Simple, Interpretable Anomaly Detectors for New Physics in Jet Substructure*, *Phys.Rev.D* **106** (3, 2022) 035014, [2203.01343]. 10

[1526] F. Canelli, A. de Cosa, L. L. Pottier, J. Niedziela, K. Pedro and M. Pierini, *Autoencoders for Semivisible Jet Detection*, *JHEP* **02** (12, 2021) 074, [2112.02864].

[1527] R. T. d'Agnolo, G. Grosso, M. Pierini, A. Wulzer and M. Zanetti, *Learning New Physics from an Imperfect Machine*, *Eur.Phys.J.C* **82** (11, 2021) 275, [2111.13633].

[1528] S. V. Chekanov and W. Hopkins, *Event-based anomaly detection for new physics searches at the LHC using machine learning*, *Universe* **8** (11, 2021) 494, [2111.12119].

[1529] C. G. Lester and R. Tombs, *Stressed GANs snag desserts, a.k.a Spotting Symmetry Violation with Symmetric Functions*, 2111.00616.

[1530] R. Tombs and C. G. Lester, *A method to challenge symmetries in data with self-supervised learning*, *JINST* **17** (11, 2021) P08024, [2111.05442].

[1531] J. A. Aguilar-Saavedra, *Anomaly detection from mass unspecific jet tagging*, *Eur.Phys.J.C* **82** (11, 2021) 130, [2111.02647].

[1532] K. Fraser, S. Homiller, R. K. Mishra, B. Ostdiek and M. D. Schwartz, *Challenges for Unsupervised Anomaly Detection in Particle Physics*, *JHEP* **03** (10, 2021) 066, [2110.06948].

[1533] B. Ostdiek, *Deep Set Auto Encoders for Anomaly Detection in Particle Physics*, *SciPost Phys.* **12** (9, 2021) 045, [2109.01695].

[1534] S. Volkovich, F. D. V. Halevy and S. Bressler, *The Data-Directed Paradigm for BSM searches*, *Eur.Phys.J.C* **82** (7, 2021) 265, [2107.11573].

[1535] G. Kasieczka, B. Nachman and D. Shih, *New Methods and Datasets for Group Anomaly Detection From Fundamental Physics*, 7, 2021. 2107.02821.

[1536] S. Caron, L. Hendriks and R. Verheyen, *Rare and Different: Anomaly Scores from a combination of likelihood and out-of-distribution models to detect new physics at the LHC*, *SciPost Phys.* **12** (6, 2021) 077, [2106.10164].

[1537] T. Dorigo, M. Fumanelli, C. Maccani, M. Mojsovska, G. C. Strong and B. Scarpa, *RanBox: Anomaly Detection in the Copula Space*, *JHEP* **01** (6, 2021) 008, [2106.05747].

[1538] A. Kahn, J. Gonski, I. Ochoa, D. Williams and G. Brooijmans, *Anomalous Jet Identification via Sequence Modeling*, *JINST* **16** (5, 2021) P08012, [2105.09274].

[1539] T. Finke, M. Krämer, A. Morandini, A. Mück and I. Oleksiyuk, *Autoencoders for unsupervised anomaly detection in high energy physics*, *JHEP* **06** (4, 2021) 161, [2104.09051].

[1540] B. M. Dillon, T. Plehn, C. Sauer and P. Sorrenson, *Better Latent Spaces for Better Autoencoders*, *SciPost Phys.* **11** (4, 2021) 061, [2104.08291].

[1541] J. H. Collins, P. Martín-Ramiro, B. Nachman and D. Shih, *Comparing Weak- and Unsupervised Methods for Resonant Anomaly Detection*, *Eur.Phys.J.C* **81** (4, 2021) 617, [2104.02092].

[1542] J. Batson, C. G. Haaf, Y. Kahn and D. A. Roberts, *Topological Obstructions to Autoencoding*, *JHEP* **04** (2, 2021) 280, [2102.08380].

[1543] P. Chakravarti, M. Kuusela, J. Lei and L. Wasserman, *Model-Independent Detection of New Physics Signals Using Interpretable Semi-Supervised Classifier Tests*, 2102.07679.

[1544] G. Stein, U. Seljak and B. Dai, *Unsupervised in-distribution anomaly detection of new physics through conditional density estimation*, 2012.11638.

[1545] D. A. Faroughy, *Uncovering hidden patterns in collider events with Bayesian probabilistic models*, *PoS* **ICHEP2020** (12, 2020) 238, [2012.08579].

[1546] S. E. Park, D. Rankin, S.-M. Udrescu, M. Yunus and P. Harris, *Quasi Anomalous Knowledge: Searching for new physics with embedded knowledge*, *JHEP* **06** (11, 2020) 030, [2011.03550].

[1547] M. van Beekveld, S. Caron, L. Hendriks, P. Jackson, A. Leinweber, S. Otten et al., *Combining outlier analysis algorithms to identify new physics at the LHC*, *JHEP* **09** (10, 2020) 024, [2010.07940].

[1548] V. Mikuni and F. Canelli, *Unsupervised clustering for collider physics*, *Phys.Rev.D* **103** (9, 2020) 092007, [2010.07106].

[1549] Adrian Alan Pol and Victor Berger and Gianluca Cerminara and Cecile Germain and Maurizio Pierini, *Anomaly Detection With Conditional Variational Autoencoders*, 2010.05531.

[1550] K. Benkendorfer, L. L. Pottier and B. Nachman, *Simulation-Assisted Decorrelation for Resonant Anomaly Detection*, *Phys.Rev.D* **104** (9, 2020) 035003, [2009.02205].

[1551] J. A. Aguilar-Saavedra, F. R. Joaquim and J. F. Seabra, *Mass Unspecific Supervised Tagging (MUST) for boosted jets*, 2008.12792.

[1552] S. Alexander, S. Gleyzer, H. Parul, P. Reddy, M. W. Toomey, E. Usai et al., *Decoding Dark Matter Substructure without Supervision*, 2008.12731.

[1553] P. Thaprasop, K. Zhou, J. Steinheimer and C. Herold, *Unsupervised Outlier Detection in Heavy-Ion Collisions*, *Phys.Scripta* **96** (7, 2020) 064003, [2007.15830].

[1554] C. K. Khosa and V. Sanz, *Anomaly Awareness*, *SciPost Phys.* **15** (7, 2020) 053, [2007.14462].

[1555] M. C. Romao, N. Castro and R. Pedro, *Finding New Physics without learning about it: Anomaly Detection as a tool for Searches at Colliders*, 2006.05432.

[1556] O. Knapp, G. Dissertori, O. Cerri, T. Q. Nguyen, J.-R. Vlimant and M. Pierini, *Adversarially Learned Anomaly Detection on CMS Open Data: re-discovering the top quark*, 2005.01598.

[1557] M. Romão Crispim, N. Castro, R. Pedro and T. Vale, *Transferability of Deep Learning Models in Searches for New Physics at Colliders*, *Phys. Rev. D* **101** (2020) 035042, [1912.04220].

[1558] J. A. Aguilar-Saavedra, J. H. Collins and R. K. Mishra, *A generic anti-QCD jet tagger*, *JHEP* **11** (2017) 163, [1709.01087].

[1559] A. Andreassen, B. Nachman and D. Shih, *Simulation Assisted Likelihood-free Anomaly Detection*, *Phys. Rev. D* **101** (2020) 095004, [2001.05001]. 10

[1560] G. M. Alessandro Casa, *Nonparametric semisupervised classification for signal detection in high energy physics*, 1809.02977.

[1561] A. Mullin, H. Pacey, M. Parker, M. White and S. Williams, *Does SUSY have friends? A new approach for LHC event analysis*, 1912.10625.

[1562] A. De Simone and T. Jacques, *Guiding New Physics Searches with Unsupervised Learning*, *Eur. Phys. J.* **C79** (2019) 289, [1807.06038].

[1563] J. Hajer, Y.-Y. Li, T. Liu and H. Wang, *Novelty Detection Meets Collider Physics*, 1807.10261.

[1564] A. Blance, M. Spannowsky and P. Waite, *Adversarially-trained autoencoders for robust unsupervised new physics searches*, *JHEP* **10** (2019) 047, [1905.10384].

[1565] O. Cerri, T. Q. Nguyen, M. Pierini, M. Spiropulu and J.-R. Vlimant, *Variational Autoencoders for New Physics Mining at the Large Hadron Collider*, *JHEP* **05** (2019) 036, [1811.10276].

[1566] T. S. Roy and A. H. Vijay, *A robust anomaly finder based on autoencoder*, 1903.02032.

[1567] T. Heimel, G. Kasieczka, T. Plehn and J. M. Thompson, *QCD or What?*, *SciPost Phys.* **6** (2019) 030, [1808.08979].

[1568] M. Farina, Y. Nakai and D. Shih, *Searching for New Physics with Deep Autoencoders*, 1808.08992.

[1569] R. T. D'Agnolo, G. Grosso, M. Pierini, A. Wulzer and M. Zanetti, *Learning Multivariate New Physics*, 1912.12155.

[1570] R. T. D'Agnolo and A. Wulzer, *Learning New Physics from a Machine*, *Phys. Rev.* **D99** (2019) 015014, [1806.02350]. 9, 11

[1571] D. Park et al., *FM4NPP: A Scaling Foundation Model for Nuclear and Particle Physics*, 2508.14087. 9

[1572] A. Saqlain and S. Kartal, *Exploring potential of OpenAI o3 as a signal-agnostic model for Signal/Background separation in $t \to uZ$ FCNC Searches at Future Hadron Colliders*, 2507.04272.

[1573] L. Tani, J. Pata and J. Birk, *Reconstructing hadronically decaying tau leptons with a jet foundation model*, *SciPost Phys.Core* **8** (3, 2025) 046, [2503.19165].

[1574] V. Mikuni and B. Nachman, *A Method to Simultaneously Facilitate All Jet Physics Tasks*, *Phys.Rev.D* **111** (2, 2025) 054015, [2502.14652].

[1575] K. G. Barman et al., *Large Physics Models: Towards a collaborative approach with Large Language Models and Foundation Models*, 2501.05382.

[1576] M. Omana Kuttan, K. Zhou, J. Steinheimer and H. Stöcker, *Towards a foundation model for heavy-ion collision experiments through point cloud diffusion*, 2412.10352.

[1577] A. J. Wildridge, J. P. Rodgers, E. M. Colbert, Y. yao, A. W. Jung and M. Liu, *Bumblebee: Foundation Model for Particle Physics Discovery*, in *38th conference on Neural Information Processing Systems*, 12, 2024. 2412.07867.

[1578] V. Mikuni and B. Nachman, *OmniLearn: A Method to Simultaneously Facilitate All Jet Physics Tasks*, *Phys.Rev.D* **111** (4, 2024) L051504, [2404.16091].

[1579] Z. Zhang et al., *Xiwu: A Basis Flexible and Learnable LLM for High Energy Physics*, 2404.08001.

[1580] C. Fanelli, J. Giroux, P. Moran, H. Nayak, K. Suresh and E. Walter, *Physics Event Classification Using Large Language Models*, *JINST* **19** (4, 2024) C07011, [2404.05752].

[1581] P. Harris, M. Kagan, J. Krupa, B. Maier and N. Woodward, *Re-Simulation-based Self-Supervised Learning for Pre-Training Foundation Models*, *Phys.Rev.D* **111** (3, 2024) 3, [2403.07066].

[1582] J. Birk, A. Hallin and G. Kasieczka, *OmniJet-α: The first cross-task foundation model for particle physics*, *Mach.Learn.Sci.Tech.* **5** (3, 2024) 035031, [2403.05618].

[1583] M. Vigl, N. Hartman and L. Heinrich, *Finetuning Foundation Models for Joint Analysis Optimization*, *Mach.Learn.Sci.Tech.* **5** (1, 2024) 025075, [2401.13536]. 9

[1584] J. Erdmann, F. Mausolf and J. L. Späh, *KAN we improve on HEP classification tasks? Kolmogorov-Arnold Networks applied to an LHC physics example*, *Comput.Softw.Big Sci.* **9** (8, 2024) 9, [2408.02743]. 9

[1585] D. Sadasivan, I. Cordero, A. Graham, C. Marsh, D. Kupcho, M. Mourad et al., *Deep Neural Network Driven Simulation Based Inference Method for Pole Position Estimation under Model Misspecification*, 2507.18824. 10

[1586] J. Villarreal, J. Woodward, J. Hardin and J. Conrad, *A Frequentist Simulation-Based Inference Treatment of Sterile Neutrino Global Fits*, 2507.01153.

[1587] A. Ghosh, M. Griese, U. Haisch and T. H. Park, *Neural simulation-based inference of the Higgs trilinear self-coupling via off-shell Higgs production*, 2507.02032.

[1588] P. Shyamsundar, *Comment on "An implementation of neural simulation-based inference for parameter estimation in ATLAS"*, 2505.19156.

[1589] I. Elsharkawy and Y. Kahn, *Contrastive Normalizing Flows for Uncertainty-Aware Parameter Estimation*, 2505.08709. 11

[1590] L. Benato, C. Giordano, C. Krause, A. Li, R. Schöfbeck, D. Schwarz et al., *Unbinned inclusive cross-section measurements with machine-learned systematic uncertainties*, 2505.05544. 11

[1591] F. T. Acosta, T. Wamorkar, V. Mikuni and B. Nachman, *Stabilizing Neural Likelihood Ratio Estimation*, 2503.20753. 10

[1592] B. Sluijter, S. Diefenbacher, W. Bhimji and B. Nachman, *Discriminative versus Generative Approaches to Simulation-based Inference*, 2503.07962.

[1593] G. B. De Luca, B. Nachman, E. Silverstein and H. Zheng, *Optimizers for Stabilizing Likelihood-free Inference*, 2501.18419. 11

[1594] J. Villarreal, J. M. Hardin and J. M. Conrad, *Feldman-Cousins' ML Cousin: Sterile Neutrino Global Fits using Simulation-Based Inference*, 2501.08988.

[1595] J. Alda, A. Mir and S. Penaranda, *Flavour anomalies and Machine Learning: an improved analysis*, 2412.15830.

[1596] ATLAS Collaboration, *An implementation of neural simulation-based inference for parameter estimation in ATLAS*, *Rept.Prog.Phys.* **88** (12, 2024) 067801, [2412.01600].

[1597] T. Heimel, T. Plehn and N. Schmal, *Profile Likelihoods on ML-Steroids*, 2411.00942. 10

[1598] H. Bahl, V. Bresó, G. De Crescenzo and T. Plehn, *Advancing Tools for Simulation-Based Inference*, 2410.07315.

[1599] R. Mastandrea, B. Nachman and T. Plehn, *Constraining the Higgs Potential with Neural Simulation-based Inference for Di-Higgs Production*, *Phys.Rev.D* **110** (5, 2024) 056004, [2405.15847].

[1600] M. A. Diaz, G. Cerro, S. Dasmahapatra and S. Moretti, *Bayesian Active Search on Parameter Space: a 95 GeV Spin-0 Resonance in the $(B-L)$SSM*, 2404.18653.

[1601] E. Alvarez, L. Da Rold, M. Szewc, A. Szynkman, S. A. Tanco and T. Tarutina, *Improvement and generalization of ABCD method with Bayesian inference*, *SciPost Phys.Core* **7** (2, 2024) 043, [2402.08001].

[1602] S. Chai, J. Gu and L. Li, *From Optimal Observables to Machine Learning: an Effective-Field-Theory Analysis of $e^+e^- \to W^+W^-$ at Future Lepton Colliders*, *JHEP* **05** (1, 2024) 292, [2401.02474].

[1603] T. Heimel, N. Huetsch, R. Winterhalder, T. Plehn and A. Butter, *Precision-Machine Learning for the Matrix Element Method*, *SciPost Phys.* **17** (10, 2023) 129, [2310.07752].

[1604] I. Espejo, S. Perez, K. Hurtado, L. Heinrich and K. Cranmer, *Scaling MadMiner with a deployment on REANA*, in *21th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI meets Reality*, 4, 2023. 2304.05814.

[1605] R. Barrué, P. Conde-Muíño, V. Dao and R. Santos, *Simulation-based inference in the search for CP violation in leptonic WH production*, *JHEP* **04** (8, 2023) 014, [2308.02882].

[1606] A. Morandini, T. Ferber and F. Kahlhoefer, *Reconstructing axion-like particles from beam dumps with simulation-based inference*, *Eur.Phys.J.C* **84** (8, 2023) 200, [2308.01353].

[1607] M. Erdogan, N. B. Baytekin, S. E. Coban and A. Demir, *Machine Learning and Kalman Filtering for Nanomechanical Mass Spectrometry*, *IEEE Sensors J.* **24** (6, 2023) 6303, [2306.00563].

[1608] D. Breitenmoser, F. Cerutti, G. Butterweck, M. M. Kasprzak and S. Mayer, *Emulator-based Bayesian Inference on Non-Proportional Scintillation Models by Compton-Edge Probing*, *Nature Commun.* **14** (2, 2023) 7790, [2302.05641].

[1609] L. Heinrich, S. Mishra-Sharma, C. Pollard and P. Windischhofer, *Hierarchical Neural Simulation-Based Inference Over Event Ensembles*, 2306.12584.

[1610] S. Rizvi, M. Pettee and B. Nachman, *Learning Likelihood Ratios with Neural Network Classifiers*, *JHEP* **02** (5, 2023) 136, [2305.10500].

[1611] M. Neubauer, M. Feickert, M. Katare and A. Roy, *Deep Learning for the Matrix Element Method*, *PoS* **ICHEP2022** (2022) 246, [2211.11910].

[1612] A. Butter, T. Heimel, T. Martini, S. Peitzsch and T. Plehn, *Two Invertible Networks for the Matrix Element Method*, *SciPost Phys.* **15** (9, 2022) 094, [2210.00019].

[1613] E. Arganda, A. D. Perez, M. de los Rios and R. M. Sandá Seoane, *Machine-Learned Exclusion Limits without Binning*, *Eur.Phys.J.C* **83** (11, 2022) 1158, [2211.04806].

[1614] K. Kong, K. T. Matchev, S. Mrenna and P. Shyamsundar, *New Machine Learning*

Techniques for Simulation-Based Inference: InferoStatic Nets, Kernel Score Estimation, and Kernel Likelihood Ratio Estimation, `2210.01680`.

[1615] E. Arganda, X. Marcano, V. M. Lozano, A. D. Medina, A. D. Perez, M. Szewc et al., *A method for approximating optimal statistical significances with machine-learned likelihoods*, *Eur.Phys.J.C* **82** (5, 2022) 993, [`2205.05952`].

[1616] H. Bahl and S. Brass, *Constraining CP-violation in the Higgs-top-quark interaction using machine-learning-based inference*, *JHEP* **03** (10, 2021) 017, [`2110.10177`].

[1617] R. K. Barman, D. Gonçalves and F. Kling, *Machine Learning the Higgs-Top CP Phase*, *Phys.Rev.D* **105** (10, 2021) 035023, [`2110.07635`].

[1618] S. Chatterjee, N. Frohner, L. Lechner, R. Schöfbeck and D. Schwarz, *Tree boosting for learning EFT parameters*, *Comput.Phys.Commun.* **277** (7, 2021) 108385, [`2107.10859`].

[1619] F. Flesher, K. Fraser, C. Hutchison, B. Ostdiek and M. D. Schwartz, *Parameter Inference from Event Ensembles and the Top-Quark Mass*, *JHEP* **09** (11, 2020) 058, [`2011.04666`].

[1620] A. Coogan, K. Karchev and C. Weniger, *Targeted Likelihood-Free Inference of Dark Matter Substructure in Strongly-Lensed Galaxies*, *34th Conference on Neural Information Processing Systems* (10, 2020) , [`2010.07032`].

[1621] A. Andreassen, S.-C. Hsu, B. Nachman, N. Suaysom and A. Suresh, *Parameter Estimation using Neural Networks in the Presence of Detector Effects*, *Phys. Rev. D* **103** (2021) 036001, [`2010.03569`].

[1622] J. Brehmer, G. Louppe, J. Pavez and K. Cranmer, *Mining gold from implicit models to improve likelihood-free inference*, *Proc. Nat. Acad. Sci.* (2020) 201915980, [`1805.12244`]. 10

[1623] J. Brehmer, F. Kling, I. Espejo and K. Cranmer, *MadMiner: Machine learning-based inference for particle physics*, *Comput. Softw. Big Sci.* **4** (2020) 3, [`1907.10621`].

[1624] J. Brehmer, K. Cranmer, G. Louppe and J. Pavez, *A Guide to Constraining Effective Field Theories with Machine Learning*, `1805.00020`.

[1625] J. Brehmer, K. Cranmer, G. Louppe and J. Pavez, *Constraining Effective Field Theories with Machine Learning*, `1805.00013`.

[1626] J. Hollingsworth and D. Whiteson, *Resonance Searches with Machine Learned Likelihood Ratios*, `2002.04699`. 10

[1627] M. Stoye, J. Brehmer, G. Louppe, J. Pavez and K. Cranmer, *Likelihood-free inference with an improved cross-entropy estimator*, `1808.00973`.

[1628] A. Andreassen and B. Nachman, *Neural Networks for Full Phase-space Reweighting and Parameter Tuning*, *Phys. Rev. D* **101** (2020) 091901, [1907.08209]. 10

[1629] A. Butter, T. Heimel, N. Huetsch, M. Kagan and T. Plehn, *Simulation-Prior Independent Neural Unfolding Procedure*, 2507.15084. 10

[1630] A. Badea et al., *Analysis note: measurement of thrust in* e^+e^- *collisions at* $\sqrt{s} = 91$ *GeV with archived ALEPH data*, 2507.14349.

[1631] A. Falcão and A. Takacs, *High-Dimensional Unfolding in Large Backgrounds*, 2507.06291.

[1632] K. Desai, O. Long and B. Nachman, *Unbinned Inference with Correlated Events*, 2504.14072. 11

[1633] R. G. Huang, A. Cudd, M. Kawaue, T. Kikawa, B. Nachman, V. Mikuni et al., *Machine Learning-Assisted Unfolding for Neutrino Cross-section Measurements*, *Phys.Rev.D* **112** (4, 2025) 012008, [2504.06857].

[1634] R. Milton, V. Mikuni, T. Lee, M. Arratia, T. Wamorkar and B. Nachman, *Tools for Unbinned Unfolding*, *JINST* **20** (3, 2025) P05034, [2503.09720].

[1635] H1 Collaboration, *Machine Learning-Assisted Measurement of Lepton-Jet Azimuthal Angular Asymmetries in Deep-Inelastic Scattering at HERA*, 2412.14092. 11

[1636] A. Butter, S. Diefenbacher, N. Huetsch, V. Mikuni, B. Nachman, S. Palacios Schweitzer et al., *Generative Unfolding with Distribution Mapping*, *SciPost Phys.* **18** (11, 2024) 200, [2411.02495].

[1637] H. Zhu, K. Desai, M. Kuusela, V. Mikuni, B. Nachman and L. Wasserman, *Multidimensional Deconvolution with Profiling*, 2409.10421.

[1638] K. Desai, B. Nachman and J. Thaler, *Moment Unfolding*, *Phys.Rev.D* **110** (7, 2024) 116013, [2407.11284].

[1639] A. Shmakov, K. Greif, M. J. Fenton, A. Ghosh, P. Baldi and D. Whiteson, *Full Event Particle-Level Unfolding with Variable-Length Latent Variational Diffusion*, *SciPost Phys.* **18** (4, 2024) 117, [2404.14332].

[1640] J. Chan and B. Nachman, *Unbinned Profiled Unfolding*, *Phys.Rev.D* **108** (2, 2023) 016002, [2302.05390].

[1641] M. Arratia, D. Britzger, O. Long and B. Nachman, *Optimizing Observables with Machine Learning for Better Unfolding*, *JINST* **17** (3, 2022) P07009, [2203.16722].

[1642] M.-L. Wong, A. Edmonds and C. Wu, *Feed-forward neural network unfolding*, 2112.08180.

[1643] M. Arratia et al., *Presenting Unbinned Differential Cross Section Results*, *JINST* **17** (9, 2021) P01024, [2109.13243].

[1644] H1 Collaboration, *Measurement of lepton-jet correlation in deep-inelastic scattering with the H1 detector using machine learning for unfolding*, *Phys.Rev.Lett.* **128** (8, 2021) 132002, [2108.12376]. 11

[1645] P. Komiske, W. P. McCormack and B. Nachman, *Preserving New Physics while Simultaneously Unfolding All Observables*, *Phys.Rev.D* **104** (5, 2021) 076027, [2105.09923].

[1646] A. Andreassen, P. T. Komiske, E. M. Metodiev, B. Nachman, A. Suresh and J. Thaler, *Scaffolding Simulations with Deep Learning for High-dimensional Deconvolution*, 2105.04448.

[1647] P. Baroň, *Comparison of Machine Learning Approach to other Unfolding Methods*, *Acta Phys.Polon.B* **52** (4, 2021) 863, [2104.03036].

[1648] G. Zech and B. Aslan, *Binning-Free Unfolding Based on Monte Carlo Migration*, *PHYSTAT* (2003) .

[1649] L. Lindemann and G. Zech, *Unfolding by weighting Monte Carlo events*, *Nucl. Instrum. Meth. A* **354** (1995) 516–521.

[1650] D. Martschei, M. Feindt, S. Honc and J. Wagner-Kuhr, *Advanced event reweighting using multivariate analysis*, *J. Phys. Conf. Ser.* **368** (2012) 012028.

[1651] A. Glazov, *Machine learning as an instrument for data unfolding*, 1712.01814.

[1652] N. D. Gagunashvili, *Machine learning approach to inverse problem and unfolding procedure*, 1004.2006.

[1653] A. Andreassen, P. T. Komiske, E. M. Metodiev, B. Nachman and J. Thaler, *OmniFold: A Method to Simultaneously Unfold All Observables*, *Phys. Rev. Lett.* **124** (2020) 182001, [1911.09107].

[1654] M. Mieskolainen, *DeepEfficiency - optimal efficiency inversion in higher dimensions at the LHC*, 1809.06101. 10

[1655] W. Chung, *Synthetic Training and Representation Bridging in Reconstruction Domains*, 2505.05664. 10

[1656] F. Mokhtar, J. Pata, M. Kagan, D. Garcia, E. Wulff, M. Zhang et al., *Fine-tuning machine-learned particle-flow reconstruction for new detector geometries in future colliders*, *Phys.Rev.D* **111** (2, 2025) 092015, [2503.00131].

[1657] D. I. Glazier and R. Tyson, *Converting sWeights to Probabilities with Density Ratios*, 2409.08183.

[1658] G. Zhao, L. Wu, F. Grancagnolo, N. De Filippis, M. Dong and S. Sun, *Peak finding algorithm for cluster counting with domain adaptation*, *Comput. Phys. Commun.* **300** (2024) 109208, [2402.16270].

[1659] M. Algren, T. Golling, M. Guth, C. Pollard and J. A. Raine, *Flow Away your Differences: Conditional Normalizing Flows as an Improvement to Reweighting*, 2304.14963.

[1660] J. S. Schreck, M. Hayman, G. Gantos, A. Bansemer and D. J. Gagne, *Mimicking non-ideal instrument behavior for hologram processing using neural style translation*, 2301.02757.

[1661] B. Camaiani, R. Seidita, L. Anderlini, R. Ceccarelli, V. Ciulli, P. Lenzi et al., *Model independent measurements of Standard Model cross sections with Domain Adaptation*, *Eur.Phys.J.C* **82** (7, 2022) 921, [2207.09293].

[1662] B. Nachman and J. Thaler, *Neural Conditional Reweighting*, *Phys.Rev.D* **105** (7, 2021) 076015, [2107.08979].

[1663] A. Rogozhnikov, *Reweighting with Boosted Decision Trees*, *Proceedings, 17th International Workshop on Advanced Computing and Analysis Techniques in Physics Research (ACAT 2016): Valparaiso, Chile, January 18-22, 2016; J. Phys. Conf. Ser.* **762** (2016) 012036, [1608.05806]. 10

[1664] J. Carzon, A. Ghosh, R. Izbicki, A. Lee, L. Masserano and D. Whiteson, *On Focusing Statistical Power for Searches and Measurements in Particle Physics*, 2507.17831. 10

[1665] M. Frank, S. Heinemeyer, M. Mühlleitner and K. Radchenko, *Experimental Determination of BSM Triple Higgs Couplings at the HL-LHC with Neural Networks*, 2506.18981.

[1666] A. Chatterjee, A. Choudhury, S. Mitra, A. Mondal and S. Mondal, *Exploring the BSM parameter space with Neural Network aided Simulation-Based Inference*, 2502.11928.

[1667] G. Grosso, D. Sengupta, T. Golling and P. Harris, *Robust resonant anomaly detection with NPLM*, 2501.01778. 11

[1668] R. Masełek, M. M. Nojiri and K. Sakurai, *Machine Learning Electroweakino Production*, *Eur.Phys.J.C* **85** (10, 2024) 605, [2411.00093].

[1669] A. Flórez, A. Gurrola, C. Rodriguez and U. S. Qureshi, *Probing Light Scalars and Vector-like Quarks at the High-Luminosity LHC*, *Eur.Phys.J.C* **85** (10, 2024) 379, [2410.17854].

[1670] R. Schöfbeck, *Refinable modeling for unbinned SMEFT analyses*, *Mach.Learn.Sci.Tech.* **6** (6, 2024) 015007, [2406.19076].

[1671] A. Hammad, P. Ko, C.-T. Lu and M. Park, *Exploring Exotic Decays of the Higgs Boson to Multi-Photons at the LHC via Multimodal Learning Approaches*, *JHEP* **09** (5, 2024) 166, [2405.18834].

[1672] I. Ahmed, S. Swalheen, M. U. Rehman and R. Tariq, *Magnetic Monopole Phenomenology at Future Hadron Colliders*, *J.Phys.G* **51** (4, 2024) 125006, [2404.10871].

[1673] D. Choudhury, K. Deka and L. K. Saini, *Boosted four-top production at the LHC : a window to Randall-Sundrum or extended color symmetry*, *Phys.Rev.D* **110** (4, 2024) 075020, [2404.04409].

[1674] R. Baruah, S. Mondal, S. K. Patra and S. Roy, *Probing intractable beyond-standard-model parameter spaces armed with Machine Learning*, *Eur.Phys.J.ST* (4, 2024) , [2404.02698].

[1675] I. Ahmed, A. Quddus, J. Muhammad, M. Shoaib and S. Shafaq, *Probing Heavy Charged Higgs Boson Using Multivariate Technique at Gamma-Gamma Collider*, *Chin.Phys.C* **49** (3, 2024) 043101, [2403.20293].

[1676] R. Catena and E. Urdshals, *Dark Matter-induced electron excitations in silicon and germanium with Deep Learning*, *Phys.Rev.D* **111** (3, 2024) L011702, [2403.07053].

[1677] S. Bhattacharya, A. Sarkar and S. Biswas, *Higgs couplings in SMEFT via Zh production at the HL-LHC*, *Phys.Rev.D* **111** (3, 2024) 11, [2403.03001].

[1678] M. van Beekveld, W. Beenakker, J. Kip, M. Schutten and D. van Vlijmen, *The impact of CP-violating phases on DM observables in the cpMSSM*, 2402.08814.

[1679] R. K. Barman, G. Bélanger, B. Bhattacherjee, R. Godbole and R. Sengupta, *Current status of the light neutralino thermal dark matter in the phenomenological MSSM*, *Phys.Rev.D* **111** (2, 2024) 015014, [2402.07991].

[1680] J. C. Romão and M. Crispim Romão, *Combining evolutionary strategies and novelty detection to go beyond the alignment limit of the Z3 3HDM*, *Phys. Rev. D* **109** (2024) 095040, [2402.07661].

[1681] E. Arganda, D. A. Díaz, A. D. Perez, R. M. Sandá Seoane and A. Szynkman, *LHC Study of Third-Generation Scalar Leptoquarks with Machine-Learned Likelihoods*, *Phys.Rev.D* **109** (9, 2023) 055032, [2309.05407].

[1682] N. Franz, M. Dennis and J. Sakstein, *Tip of the Red Giant Branch Bounds on the Neutrino Magnetic Dipole Moment Revisited*, 2307.13050.

[1683] T. Mandal, A. Masaye, S. Mitra, C. Neeraj, N. Reule and K. Shah, *Pinning down the leptophobic Z' in leptonic final states with Deep Learning*, *Phys.Lett.B* **849** (7, 2023) 138417, [2307.01118].

[1684] S. S. Chhibra, N. Chernyavskaya, B. Maier, M. Pierini and S. Hasan, *Autoencoders for Real-Time SUEP Detection*, *Eur.Phys.J.Plus* **139** (6, 2023) 281, [2306.13595].

[1685] M. van Beekveld, P. Grace, A. Kvellestad, A. Leinweber and M. White, *Simple, but* *not simplified: A new approach for optimising beyond-Standard Model physics searches at the Large Hadron Collider*, 2305.01835.

[1686] M. T. Dennis and J. Sakstein, *Tip of the Red Giant Branch Bounds on the Axion-Electron Coupling Revisited*, 2305.03113.

[1687] R. Gomez Ambrosio, J. ter Hoeve, M. Madigan, J. Rojo and V. Sanz, *Unbinned multivariate observables for global SMEFT analyses from machine learning*, *JHEP* **03** (11, 2022) 033, [2211.02058].

[1688] F. A. de Souza, M. Crispim Romão, N. F. Castro, M. Nikjoo and W. Porod, *Exploring Parameter Spaces with Artificial Intelligence and Machine Learning Black-Box Optimisation Algorithms*, *Phys.Rev.D* **107** (6, 2022) 035004, [2206.09223]. 10

[1689] K. Braga, M. Diefenthaler, S. Goldenberg, D. Lersch, Y. Li, J.-W. Qiu et al., *Toward an event-level analysis of hadron structure using differential programming*, 2507.15768. 10

[1690] K. A. Wozniak, S. Mulligan, J. Kieseler, M. Klute, F. Fleuret and T. Golling, *End-to-End Optimal Detector Design with Mutual Information Surrogates*, 2503.14342.

[1691] N. Heller, P. Ilten, T. Menzo, S. Mrenna, B. Nachman, A. Siodmok et al., *Rejection Sampling with Autodifferentiation – Case study: Fitting a Hadronization Model*, 2411.02194.

[1692] W. Chung, *Full Detector Simulation of a Projective Dual-Readout Segmented Crystal Electromagnetic Calorimeter with Precision Timing*, in *20th International Conference on Calorimetry in Particle Physics*, vol. 320, p. 00052, 8, 2024. 2408.11027. DOI.

[1693] P. Barham Alzás and R. Radev, *Differentiable nuclear deexcitation simulation for low energy neutrino physics*, in *Prospects in Neutrinos Physics*, 3, 2024. 2404.00180.

[1694] M. Aehle et al., *Progress in End-to-End Optimization of Detectors for Fundamental Physics with Differentiable Programming*, *Rev.Phys.* (9, 2023) , [2310.05673].

[1695] M. Kagan and L. Heinrich, *Branches of a Tree: Taking Derivatives of Programs with Discrete and Branching Randomness in High Energy Physics*, 2308.16680.

[1696] R. Shenoy, J. Duarte, C. Herwig, J. Hirschauer, D. Noonan, M. Pierini et al., *Differentiable Earth Mover's Distance for Data Compression at the High-Luminosity LHC*, *Mach.Learn.Sci.Tech.* **4** (6, 2023) 045058, [2306.04712].

[1697] F. Napolitano et al., *Novel Machine Learning and Differentiable Programming*

Techniques applied to the VIP-2 Underground Experiment, *Measur.Sci.Tech.* **35** (5, 2023) 025501, [2305.17153].

[1698] B. Nachman and S. Prestel, *Morphing parton showers with event derivatives*, 2208.02274.

[1699] MODE collaboration, T. Dorigo et al., *Toward the end-to-end optimization of particle physics instruments with differentiable programming*, *Rev. Phys.* **10** (2023) 100085, [2203.13818].

[1700] L. Heinrich and M. Kagan, *Differentiable Matrix Elements with MadJax*, in *20th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI Decoded - Towards Sustainable, Diverse, Performant and Effective Scientific Computing*, vol. 2438, p. 012137, 2, 2022. 2203.00057. DOI. 10

[1701] A. J. Larkoski, *A Step Toward Interpretability: Smearing the Likelihood*, *JHEP* **03** (1, 2025) 198, [2501.07643]. 10

[1702] A. Gavrikov et al., *Interpretable machine learning approach for electron antineutrino selection in a large liquid scintillator detector*, *Phys.Lett.B* **860** (6, 2024) 139141, [2406.12901].

[1703] J. J. H. Wilkinson and C. G. Lester, *Statistical divergences in high-dimensional hypothesis testing and a modern technique for estimating them*, 2405.06397.

[1704] T. Mengel, P. Steffanic, C. Hughes, A. C. O. da Silva and C. Nattrass, *Interpretable Machine Learning Methods Applied to Jet Background Subtraction in Heavy Ion Collisions*, *Phys.Rev.C* **108** (3, 2023) L021901, [2303.08275].

[1705] K. G. Barman, S. Caron, T. Claassen and H. de Regt, *Towards a Benchmark for Scientific Understanding in Humans and Machines*, *Minds Machines* **34** (2024) 6, [2304.10327].

[1706] A. Roy and M. S. Neubauer, *Interpretability of an Interaction Network for identifying $H \to b\bar{b}$ jets*, *PoS* **ICHEP2022** (11, 2022) 223, [2211.12770].

[1707] A. Khot, M. S. Neubauer and A. Roy, *A Detailed Study of Interpretability of Deep Neural Network based Top Taggers*, *Mach.Learn.Sci.Tech.* **4** (10, 2022) 035003, [2210.04371].

[1708] C. Grojean, A. Paul, Z. Qian and I. Strümke, *Lessons on interpretable machine learning from particle physics*, *Nature Rev. Phys.* **4** (2022) 284–286, [2203.08021].

[1709] L. Anzalone, T. Diotalevi and D. Bonacorsi, *Improving Parametric Neural Networks for High-Energy Physics (and Beyond)*, 2202.00424.

[1710] F. Mokhtar, R. Kansal, D. Diaz, J. Duarte, J. Pata, M. Pierini et al., *Explaining machine-learned particle-flow reconstruction*, in *35th Conference on Neural Information Processing Systems*, 11, 2021. 2111.12840.

[1711] G. Agarwal, L. Hay, I. Iashvili, B. Mannix, C. McLean, M. Morris et al., *Explainable AI for ML jet taggers using expert variables and layerwise relevance propagation*, *JHEP* **05** (11, 2020) 208, [2011.13466].

[1712] S. Chang, T. Cohen and B. Ostdiek, *What is the Machine Learning?*, *Phys. Rev.* **D97** (2018) 056009, [1709.10106]. 10

[1713] S. Benevedes and J. Thaler, *Frequentist Uncertainties on Neural Density Ratios with wifi Ensembles*, 2506.00113. 11

[1714] I. Elsharkawy, Y. Kahn and B. Hooberman, *Uncertainty Quantification From Scaling Laws in Deep Neural Networks*, 2503.05938.

[1715] S. Bieringer, S. Diefenbacher, G. Kasieczka and M. Trabs, *Calibrating Bayesian Generative Machine Learning for Bayesiamplification*, *Mach.Learn.Sci.Tech.* **5** (8, 2024) 045044, [2408.00838].

[1716] A. Golutvin, A. Iniukhin, A. Mauri, P. Owen, N. Serra and A. Ustyuzhanin, *The DL Advocate: Playing the devil's advocate with hidden systematic uncertainties*, *Eur.Phys.J.C* **83** (3, 2023) 779, [2303.15956].

[1717] D. Koh, A. Mishra and K. Terao, *Deep Neural Network Uncertainty Quantification for LArTPC Reconstruction*, *JINST* **18** (2, 2023) P12013, [2302.03787].

[1718] K. Cheung, Y.-L. Chung, S.-C. Hsu and B. Nachman, *Exploring the Universality of Hadronic Jet Classification*, *Eur.Phys.J.C* **82** (4, 2022) 1162, [2204.03812].

[1719] M. Bellagente, M. Haußmann, M. Luchmann and T. Plehn, *Understanding Event-Generation Networks via Uncertainties*, *SciPost Phys.* **13** (4, 2021) 003, [2104.04543].

[1720] B. Nachman and C. Shimmin, *AI Safety for High Energy Physics*, 1910.08606.

[1721] B. Nachman, *A guide for deploying Deep Learning in LHC searches: How to achieve optimality and account for uncertainty*, 1909.03081. 11

[1722] A. Azakli and B. Stelzer, *Approaching Maximal Information Extraction in Low-Signal Regimes via Multiple Instance Learning*, 2508.07114. 11

[1723] A. Stein, X. Coubez, S. Mondal, A. Novak and A. Schmidt, *Improving robustness of jet tagging algorithms with adversarial training*, *Comput.Softw.Big Sci.* **6** (3, 2022) 15, [2203.13890].

[1724] V. Estrade, C. Germain, I. Guyon and D. Rousseau, *Adversarial learning to eliminate systematic errors: a case study in High Energy Physics*, 2017. 11

[1725] F. Frohnert, D. L. B. Sombrillo, E. van Nieuwenburg and P. Emonts, *Learning Pole Structures of Hadronic States using Predictive Uncertainty Estimation*, 2507.07668. 11

[1726] CMS Collaboration, *Development of systematic uncertainty-aware neural network trainings for binned-likelihood analyses at the LHC*, 2502.13047.

[1727] L. Layer, T. Dorigo and G. Strong, *Application of Inferno to a Top Pair Cross Section Measurement with CMS Open Data*, 2301.10358.

[1728] N. Simpson and L. Heinrich, *neos: End-to-End-Optimised Summary Statistics for High Energy Physics*, in *20th International Workshop on Advanced Computing and Analysis Techniques in Physics Research: AI Decoded - Towards Sustainable, Diverse, Performant and Effective Scientific Computing*, 3, 2022. 2203.05570. DOI.

[1729] F. Abudinén et al., *Punzi-loss: A non-differentiable metric approximation for sensitivity optimisation in the search for new particles*, *Eur.Phys.J.C* **82** (10, 2021) 121, [2110.00810].

[1730] A. Ghosh, B. Nachman and D. Whiteson, *Uncertainty Aware Learning for High Energy Physics*, *Phys.Rev.D* **104** (5, 2021) 056026, [2105.08742].

[1731] S. Wunsch, S. Jörger, R. Wolf and G. Quast, *Optimal statistical inference in the presence of systematic uncertainties using neural network optimization based on binned Poisson likelihoods with nuisance parameters*, 2003.07186.

[1732] P. De Castro and T. Dorigo, *INFERNO: Inference-Aware Neural Optimisation*, *Comput. Phys. Commun.* **244** (2019) 170–179, [1806.04743].

[1733] S. Bollweg, M. Haußmann, G. Kasieczka, M. Luchmann, T. Plehn and J. Thompson, *Deep-Learning Jets with Uncertainties and More*, *SciPost Phys.* **8** (2020) 006, [1904.10004].

[1734] S. Caron, T. Heskes, S. Otten and B. Stienen, *Constraining the Parameters of High-Dimensional Models with Active Learning*, *Eur. Phys. J.* **C79** (2019) 944, [1905.08628]. 11

[1735] G. Huang and K. Zhou, *The Neural Networks with Tensor Weights and the Corresponding Fermionic Quantum Field Theory*, 2507.05303. 11

[1736] C. Ferko and J. Halverson, *Quantum Mechanics and Neural Networks*, 2504.05462.

[1737] D. Lee, H.-S. Lee and J. Yi, *Neural Network/de Sitter Space Correspondence*, *Phys.Rev.D* **112** (3, 2025) L031902, [2503.08827].

[1738] C. Park, M. Favoni, B. Lucini and G. Aarts, *Random Matrix Theory for Stochastic Gradient Descent*, *PoS* **LATTICE2024** (2025) 031, [2412.20496].

[1739] Z. Zhang, *Neural Scaling Laws From Large-N Field Theory: Solvable Model Beyond the Ridgeless Limit*, *Mach.Learn.Sci.Tech.* **6** (5, 2024) 025010, [2405.19398].

[1740] J. Halverson and F. Ruehle, *Metric Flows with Neural Networks*, 2310.19870. 11

[1741] M. Demirtas, J. Halverson, A. Maiti, M. D. Schwartz and K. Stoner, *Neural Network Field Theories: Non-Gaussianity, Actions, and Locality*, *Mach.Learn.Sci.Tech.* **5** (7, 2023) 015002, [2307.03223].

[1742] P. Kumar, T. Mandal and S. Mondal, *Black holes and the loss landscape in machine learning*, *JHEP* **10** (6, 2023) 107, [2306.14817].

[1743] W. A. Zúñiga Galindo, *A Correspondence Between Deep Boltzmann Machines and p-Adic Statistical Field Theories*, *Adv.Theor.Math.Phys.* **28** (6, 2023) 679, [2306.03751].

[1744] I. Banta, T. Cai, N. Craig and Z. Zhang, *Structures of Neural Network Effective Theories*, *Phys.Rev.D* **109** (5, 2023) 105007, [2305.02334].

[1745] W. A. Zúñiga Galindo, C. He and B. A. Zambrano-Luna, *p-Adic statistical field theory and convolutional deep Boltzmann machines*, *PTEP* **2023** (2023) 063A01, [2302.03817].

[1746] H. Erbin, V. Lahoche and D. O. Samary, *Renormalization in the neural network-quantum field theory correspondence*, 12, 2022. 2212.11811. 11

[1747] C. Ran, S.-F. Wu and Z.-Y. Xian, *Learning geometries beyond asymptotic AdS*, 2508.05808. 11

[1748] S. Sen and V. Vaidya, *Viability of perturbative expansion for quantum field theories on neurons*, 2508.03810.

[1749] S. Li and Y. Zhang, *Exact CHY Integrand Construction Using Combinatorial Neural Networks and Discrete Optimization*, 2508.02248.

[1750] K. Braga, N. Sato and A. P. Szczepaniak, *Variational Neural Network Approach to QFT in the Field Basis*, 2508.00173.

[1751] X. Chen, Y. Chen and K. Zhou, *Data-Driven Einstein-Dilaton Model for Pure Yang-Mills Thermodynamics and Glueball Spectrum*, 2507.06729.

[1752] S.-J. Lee and A. Lukas, *Approximate Ricci-flat Metrics for Calabi-Yau Manifolds*, 2506.15766.

[1753] N. Brady, D. Tennyson and T. Vandermeulen, *Machine Learning the 6d Supergravity Landscape*, 2505.16131.

[1754] K. M. Keita and Y. H. Dicko, *Machine Learning Calabi-Yau Three-Folds, Four-Folds, and Five-Folds*, 2503.00139.

[1755] E. Hirst, T. S. Gherardini and A. G. Stapleton, *AInstein: Numerical Einstein Metrics via Machine Learning*, 2502.13043.

[1756] Y. S. Koay, R. Enberg, S. Moretti and E. Camargo-Molina, *Generating particle physics Lagrangians with transformers*, 2501.09729. 11

[1757] T. Cai, F. Charton, K. Cranmer, L. J. Dixon, G. W. Merz and M. Wilhelm, *Recurrent Features of Amplitudes in Planar $\mathcal{N} = 4$ Super Yang-Mills Theory*, *JHEP* **04** (1, 2025) 143, [2501.05743].

[1758] G. B. De Luca, *Machine Learning Gravity Compactifications on Negatively Curved Manifolds*, 2501.00093.

[1759] V. Mirjanić and C. Mishra, *Symbolic Approximations to Ricci-flat Metrics Via Extrinsic Symmetries of Calabi-Yau Hypersurfaces*, *Mach.Learn.Sci.Tech.* **6** (12, 2024) 035029, [2412.19778].

[1760] M. A. Gumus, D. Leflot, P. Tourkine and A. Zhiboedov, *The S-matrix bootstrap with neural optimizers I: zero double discontinuity*, *JHEP* **07** (12, 2024) 210, [2412.09610].

[1761] R.-K. Seong, *Generative AI for Brane Configurations, Tropical Coamoeba and 4d N=1 Quiver Gauge Theories*, *Phys.Rev.D* **111** (11, 2024) 086013, [2411.16033].

[1762] V. Vanchurin, *Emergent field theories from neural networks*, 2411.08138.

[1763] S. Kawai and N. Okada, *Truth, beauty, and goodness in grand unification: a machine learning approach*, *Phys.Lett.B* **860** (11, 2024) 139221, [2411.06718].

[1764] G. Butbaia, D. Mayorga Peña, J. Tan, P. Berglund, T. Hübsch, V. Jejjala et al., *cymyc – Calabi-Yau Metrics, Yukawas, and Curvature*, *JHEP* **03** (10, 2024) 028, [2410.19728].

[1765] C. H. Ek, O. Kim and C. Mishra, *Calabi-Yau metrics through Grassmannian learning and Donaldson's algorithm*, 2410.11284.

[1766] F. Bhat, D. Chowdhury, A. P. Saha and A. Sinha, *Bootstrapping string models with entanglement minimization and Machine-Learning*, *Phys.Rev.D* **111** (9, 2024) 066013, [2409.18259].

[1767] P. Capuozzo, T. S. Gherardini and B. Suzzoni, *Machine Learning Toric Duality in Brane Tilings*, 2409.15251.

[1768] J. Halverson, J. Naskar and J. Tian, *Conformal Fields from Neural Networks*, 2409.12222.

[1769] C. Cheung, A. Dersy and M. D. Schwartz, *Learning the Simplicity of Scattering Amplitudes*, *SciPost Phys.* **18** (8, 2024) 040, [2408.04720].

[1770] H. L. Dao, *Deep Learning Calabi-Yau four folds with hybrid and recurrent neural network architectures*, *Nucl.Phys.B* **1013** (5, 2024) 116832, [2405.17406].

[1771] S. Gukov and R.-K. Seong, *Learning BPS Spectra and the Gap Conjecture*, *Phys.Rev.D* **110** (5, 2024) 046016, [2405.09993].

[1772] G. Lopes Cardoso, D. Mayorga Peña and S. Nampuri, *Classical integrability in the presence of a cosmological constant: analytic and machine learning results*, *Fortsch.Phys.* **2025** (4, 2024) 2400267, [2404.18247].

[1773] K. M. Keita, *On Machine Learning Complete Intersection Calabi-Yau 3-folds*, *Phys.Rev.D* **110** (4, 2024) 126002, [2404.11710].

[1774] P. Hou, T. Wang, D. Cerkoney, X. Cai, Z. Li, Y. Deng et al., *Feynman Diagrams as Computational Graphs*, 2403.18840.

[1775] P.-H. Balduf and K. Shaban, *Predicting Feynman periods in ϕ^4-theory*, *JHEP* **11** (3, 2024) 038, [2403.16217].

[1776] Y. Bea, R. Jimenez, D. Mateos, S. Liu, P. Protopapas, P. Tarancón-Álvarez et al., *Gravitational Duals from Equations of State*, *JHEP* **07** (3, 2024) 087, [2403.14763].

[1777] P. Orman, H. Gharibyan and J. Preskill, *Quantum chaos in the sparse SYK model*, *JHEP* **02** (3, 2024) 173, [2403.13884].

[1778] K. Hashimoto, Y. Hirono, J. Maeda and J. Totsuka-Yoshinaka, *Neural network representation of quantum systems*, *Mach.Learn.Sci.Tech.* **5** (3, 2024) 045039, [2403.11420].

[1779] S. Lanza, *Neural Network Learning and Quantum Gravity*, *JHEP* **07** (3, 2024) 105, [2403.03245].

[1780] S. Gukov, J. Halverson and F. Ruehle, *Rigor with machine learning from field theory to the Poincaré conjecture*, *Nature Rev. Phys.* **6** (2024) 310–319, [2402.13321].

[1781] D. S. Berman, M. S. Klinger and A. G. Stapleton, *NCoder – A Quantum Field Theory approach to encoding data*, *Mach.Learn.Sci.Tech.* **6** (2, 2024) 025059, [2402.00944].

[1782] A. Constantin, C. S. Fraser-Taliente, T. R. Harvey, A. Lukas and B. Ovrut, *Computation of Quark Masses from String Theory*, *Nucl.Phys.B* **1010** (2, 2024) 116778, [2402.01615].

[1783] K. Ishiguro, S. Nishimura and H. Otsuka, *Autoencoder-Driven Clustering of Intersecting D-brane Models via Tadpole Charge*, *JHEP* **08** (12, 2023) 133, [2312.07181].

[1784] E. Hirst and T. S. Gherardini, *Calabi-Yau Four/Five/Six-folds as $\mathbb{P}^n_{\boldsymbol{w}}$ Hypersurfaces: Machine Learning, Approximation, and Generation*, *Phys.Rev.D* **109** (11, 2023) 106006, [2311.17146].

[1785] H. Erbin and R. Finotello, *Deep learning complete intersection Calabi-Yau manifolds*, 2311.11847.

[1786] S. Lanza, *Machine learning the breakdown of tame effective theories*, *Eur.Phys.J.C* **84** (11, 2023) 631, [2311.03437].

[1787] K. T. Matchev, K. Matcheva, P. Ramond and S. Verner, *Seeking Truth and Beauty in Flavor Physics with Machine Learning*, in *37th Conference on Neural Information Processing Systems*, 10, 2023. 2311.00087.

[1788] E. Choi and R.-K. Seong, *Machine Learning Regularization for the Minimum Volume Formula of Toric Calabi-Yau 3-folds*, *Phys.Rev.D* **109** (10, 2023) 046015, [2310.19276].

[1789] R. Alawadhi, D. Angella, A. Leonardo and T. S. Gherardini, *Constructing and Machine Learning Calabi-Yau Five-folds*, *Fortsch.Phys.* **72** (10, 2023) 2300262, [2310.15966].

[1790] G. N. Wojcik, *BFBrain: Scalar Bounded-From-Below Conditions from Bayesian Active Learning*, *Phys.Rev.D* **109** (9, 2023) 095018, [2309.10959].

[1791] R.-K. Seong, *Unsupervised Machine Learning Techniques for Exploring Tropical Coamoeba, Brane Tilings and Seiberg Duality*, *Phys.Rev.D* **108** (9, 2023) 106009, [2309.05702].

[1792] A. Gnech, B. Fore and A. Lovato, *Distilling the essential elements of nuclear binding via neural-network quantum states*, *Phys.Rev.Lett.* **133** (8, 2023) 142501, [2308.16266].

[1793] A. Dersy, M. D. Schwartz and A. Zhiboedov, *Reconstructing S-matrix Phases with Machine Learning*, *JHEP* **05** (8, 2023) 200, [2308.09451].

[1794] R. T. Forestano, K. T. Matchev, K. Matcheva, A. Roman, E. B. Unlu and S. Verner, *Accelerated Discovery of Machine-Learned Symmetries: Deriving the Exceptional Lie Groups G2, F4 and E6*, *Phys.Lett.B* **847** (7, 2023) 138266, [2307.04891].

[1795] R. Dorrill and J. Felis, *Macroscopic Dynamics of Entangled 3+1-Dimensional Systems: A Novel Investigation Into Why My MacBook Cable Tangles in My Backpack Every Single Day*, 2304.00220.

[1796] S. Lal, S. Majumder and E. Sobko, *The R-mAtrIx Net*, *Mach.Learn.Sci.Tech.* **5** (4, 2023) 035003, [2304.07247].

[1797] Y.-H. He, E. Heyes and E. Hirst, *Machine Learning in Physics and Geometry*, *Handbook of Statistics* **49** (3, 2023) 47, [2303.12626].

[1798] M.-W. Cheung, P.-P. Dechant, Y.-H. He, E. Heyes, E. Hirst and J.-R. Li, *Clustering Cluster Algebras with Clusters*, *Adv.Theor.Math.Phys.* **27** (12, 2022) 797, [2212.09771].

[1799] S. Chen, Y.-H. He, E. Hirst, A. Nestor and A. Zahabi, *Mahler Measuring the Genetic Code of Amoebae*, *Adv.Theor.Math.Phys.* **27** (12, 2022) 1405, [2212.06553].

[1800] E. Escalante-Notario, I. Portillo-Castillo and S. Ramos-Sanchez, *Autoencoding heterotic orbifolds with arbitrary geometry*, *J.Phys.Comm.* **8** (12, 2022) 025003, [2212.00821].

[1801] M. Gerdes and S. Krippendorf, *CYJAX: A package for Calabi-Yau metrics with JAX*, *Mach. Learn. Sci. Tech.* **4** (2023) 025031, [2211.12520].

[1802] H. Erbin and A. H. Fırat, *Characterizing 4-string contact interaction using machine learning*, *JHEP* **04** (11, 2022) 016, [2211.09129].

[1803] P. Berglund, G. Butbaia, T. Hübsch, V. Jejjala, D. Mayorga Peña, C. Mishra et al., *Machine Learned Calabi-Yau Metrics and Curvature*, *Adv.Theor.Math.Phys.* **27** (11, 2022) 1107, [2211.09801]. 11

[1804] D. Douglas, A. Mishra, D. Ratner, F. Petersen and K. Terao, *Uncertainty Propagation within Chained Models for Machine Learning Reconstruction of Neutrino-LAr Interactions*, 2411.09864. 11

[1805] S. O. Kara and S. Akkoyun, *A Search for Leptonic Photon, Z_l, at All Three CLIC Energy Stages by Using Artificial Neural Networks (ANN)*, *Acta Phys. Polon. B* **55** (2024) 6–A4, [2406.10097].

[1806] ALICE Collaboration, *Particle identification with machine learning from incomplete data in the ALICE experiment*, in *Artificial Intelligence for the Electron Ion Collider*, vol. 19, p. C07013, 3, 2024. 2403.17436. DOI.

[1807] D. Palo and W. Molzon, *Neural Network Applications to Improve Drift Chamber Track Position Measurements*, *Nucl.Instrum.Meth.A* **1064** (11, 2023) 169404, [2311.15541].

[1808] ATLAS Collaboration, *Simultaneous energy and mass calibration of large-radius jets with the ATLAS detector using a deep neural network*, *Mach.Learn.Sci.Tech.* **5** (11, 2023) 035051, [2311.08885].

[1809] S. Grönroos, M. Pierini and N. Chernyavskaya, *Automated visual inspection of CMS HGCAL silicon sensor surface using an ensemble of a deep convolutional autoencoder and classifier*, *Mach.Learn.Sci.Tech.* **4** (3, 2023) 035028, [2303.15319].

[1810] NEOS-II Collaboration, *Pulse shape discrimination using a convolutional neural network for organic liquid scintillator signals*, *JINST* **18** (2023) P03003, [2211.07892].

[1811] J. Yang, Y. Tian, W. Dai, M. Yang, L. Jiang, J. Wen et al., *A feasibility study of multi-electrode high-purity germanium detector for ^{76}Ge neutrinoless double beta decay searching*, *JINST* **18** (2023) P05025, [2211.06180].

[1812] CMS Collaboration, *Identification of hadronic tau lepton decays using a deep neural network*, *JINST* **17** (1, 2022) P07023, [2201.08458]. 11

[1813] BESIII Collaboration, *Search for the radiative leptonic decay $D^+ \to \gamma e^+ \nu_e$ with Deep Learning*, 2503.16070. 11

[1814] CMS Collaboration, *Evidence for CP violation and measurement of CP-violating parameters in $B^0_s \to J/\psi\,\phi(1020)$ decays in pp collisions at $\sqrt{s} = 13$ TeV*, 2412.19952.

[1815] ATLAS Collaboration, *Search for vector-like leptons coupling to first- and second-generation Standard Model leptons in pp collisions at $\sqrt{s} = 13$ TeV with the ATLAS detector*, *JHEP* **05** (11, 2024) 075, [2411.07143].

[1816] ATLAS Collaboration, *Accuracy versus precision in boosted top tagging with the ATLAS detector*, *JINST* **19** (7, 2024) P08018, [2407.20127].

[1817] CMS Collaboration, *Measurement of boosted Higgs bosons produced via vector boson fusion or gluon fusion in the $H \to b\bar{b}$ decay mode using LHC proton-proton collision data at $\sqrt{s} = 13$ TeV*, *JHEP* **12** (7, 2024) 035, [2407.08012].

[1818] ALICE Collaboration, *Shower Separation in Five Dimensions for Highly Granular Calorimeters using Machine Learning*, *JINST* **19** (6, 2024) P10027, [2407.00178].

[1819] MicroBooNE collaboration, P. Abratenko et al., *Improving neutrino energy estimation of charged-current interaction events with recurrent neural networks in MicroBooNE*, *Phys.Rev.D* **110** (6, 2024) 092010, [2406.10123].

[1820] ATLAS Collaboration, *A simultaneous unbinned differential cross section measurement of twenty-four Z+jets kinematic observables with the ATLAS detector*, *Phys.Rev.Lett.* **133** (5, 2024) 261803, [2405.20041].

[1821] CMS Collaboration, *Dark sector searches with the CMS experiment*, *Phys.Rept.* **1115** (5, 2024) 448, [2405.13778].

[1822] Belle-II Collaboration, *Test of light-lepton universality in τ decays with the Belle II experiment*, *JHEP* **08** (5, 2024) 205, [2405.14625].

[1823] ATLAS Collaboration, *ATLAS searches for additional scalars and exotic Higgs boson decays with the LHC Run 2 dataset*, *Phys.Rept.* **1116** (5, 2024) 184, [2405.04914].

[1824] CMS Collaboration, *Search for new resonances decaying to pairs of merged diphotons in proton-proton collisions at $\sqrt{s} = 13$ TeV*, *Phys.Rev.Lett.* **134** (5, 2024) 041801, [2405.00834].

[1825] ATLAS Collaboration, *Search for a resonance decaying into a scalar particle and a Higgs boson in the final state with two bottom quarks and two photons in proton-proton collisions at a center of mass energy of 13 TeV with the ATLAS detector*, *JHEP* **11** (4, 2024) 047, [2404.12915].

[1826] CMS Collaboration, *Search for Higgs Boson Pair Production with One Associated*

Vector Boson in Proton-Proton Collisions at $\sqrt{s}$ = 13 TeV, *JHEP* **10** (4, 2024) 061, [2404.08462].

[1827] ATLAS Collaboration, *Exploration at the high-energy frontier: ATLAS Run 2 searches investigating the exotic jungle beyond the Standard Model*, *Phys.Rept.* **1116** (3, 2024) 301, [2403.09292].

[1828] ATLAS Collaboration, *Observation of electroweak production of W^+W^- in association with jets in proton-proton collisions at $\sqrt{s} = 13$ TeV with the ATLAS Detector*, *JHEP* **07** (3, 2024) 254, [2403.04869].

[1829] CMS Collaboration, *Search for long-lived particles using displaced vertices and missing transverse momentum in proton-proton collisions at $\sqrt{s}$ = 13 TeV*, *Phys.Rev.D* **109** (2, 2024) 112005, [2402.15804].

[1830] ATLAS Collaboration, *Search for new phenomena with top-quark pairs and large missing transverse momentum using 140 fb^{-1} of pp collision data at $\sqrt{s}$ = 13 TeV with the ATLAS detector*, *JHEP* **03** (2024) 139, [2401.13430].

[1831] CMS Collaboration, *CMS highlights on searches for new physics in final states with jets*, *PoS* **LHCP2023** (2024) 162, [2401.07172].

[1832] T. B. Collaboration, *Novel techniques for alpha/beta pulse shape discrimination in Borexino*, *Phys.Rev.D* **109** (10, 2023) 112014, [2310.11826].

[1833] S. Akar, M. Elashri, R. B. Garg, E. Kauffman, M. Peters, H. Schreiner et al., *Advances in developing deep neural networks for finding primary vertices in proton-proton collisions at the LHC*, *EPJ Web Conf.* **295** (9, 2023) 09003, [2309.12417].

[1834] Y. C. Tung et al., *Suppression of Neutron Background using Deep Neural Network and Fourier Frequency Analysis at the KOTO Experiment*, *Nucl.Instrum.Meth.A* **1059** (9, 2023) 169010, [2309.12063].

[1835] ATLAS Collaboration, *Searches for supersymmetric particles with prompt decays with the ATLAS detector*, in *30th International Workshop on Deep-Inelastic Scattering and Related Subjects*, 6, 2023. 2306.15014.

[1836] NOvA Collaboration, *Measurement of $\nu\mu$ charged-current inclusive $\pi 0$ production in the NOvA near detector*, *Phys. Rev. D* **107** (2023) 112008, [2306.04028].

[1837] ATLAS Collaboration, *Evidence of off-shell Higgs boson production from ZZ leptonic decay channels and constraints on its total width with the ATLAS detector*, *Phys.Lett.B* **846** (4, 2023) 138223, [2304.01532].

[1838] ATLAS Collaboration, *Search for third-generation vector-like leptons in pp collisions at $\sqrt{s} = 13$ TeV with the ATLAS detector*, *JHEP* **07** (2023) 118, [2303.05441].

[1839] A. Collaboration, *Search for a light charged Higgs boson in $t \to H^{\pm}b$ decays, with $H^{\pm} \to cb$, in the lepton+jets final state in proton-proton collisions at $\sqrt{s} = 13$ TeV with the ATLAS detector*, *JHEP* **09** (2, 2023) 004, [2302.11739].

[1840] ATLAS Collaboration, *Observation of single-top-quark production in association with a photon using the ATLAS detector*, *Phys.Rev.Lett.* **131** (2, 2023) 181901, [2302.01283].

[1841] ATLAS Collaboration, *Search for a new Z' gauge boson in 4μ events with the ATLAS experiment*, *JHEP* **07** (2023) 090, [2301.09342].

[1842] ATLAS Collaboration, *Search for periodic signals in the dielectron and diphoton invariant mass spectra using 139 fb^{-1} of pp collisions at $\sqrt{s} = 13$ TeV with the ATLAS detector*, *JHEP* **10** (5, 2023) 079, [2305.10894].

[1843] CMS Collaboration, *Search for long-lived particles using out-of-time trackless jets in proton-proton collisions at $\sqrt{s} = 13$ TeV*, *JHEP* **07** (2023) 210, [2212.06695].

[1844] CMS Collaboration, *Evidence for Four-Top Quark Production at the LHC*, in *15th International Workshop on Top Quark Physics*, 12, 2022. 2212.06075. 11

[1845] CMS Collaboration, *Measurement of the cross section of top quark-antiquark pair production in association with a W boson in proton-proton collisions at $\sqrt{s} = 13$ TeV*, 2212.03770.

[1846] T. Li, Y. Chen, S. Wang, K. Han, H. Lin, K. Ni et al., *Reconstruction of the event vertex in the PandaX-III experiment with convolution neural network*, *JHEP* **05** (2023) 200, [2211.14992].

[1847] CMS Collaboration, *Search for Higgs Boson and Observation of Z Boson through their Decay into a Charm Quark-Antiquark Pair in Boosted Topologies in Proton-Proton Collisions at s=13 TeV*, *Phys. Rev. Lett.* **131** (2023) 041801, [2211.14181].

[1848] MicroBooNE Collaboration, *Search for an anomalous excess of charged-current quasi-elastic ν_e interactions with the MicroBooNE experiment using Deep-Learning-based reconstruction*, *Phys.Rev.D* **105** (10, 2021) 112003, [2110.14080].

[1849] MicroBooNE Collaboration, *Search for an anomalous excess of inclusive charged-current ν_e interactions in the MicroBooNE experiment using Wire-Cell reconstruction*, *Phys.Rev.D* **105** (10, 2021) 112005, [2110.13978].

[1850] C. Collaboration, *A deep neural network to search for new long-lived particles decaying to jets*, *Mach. Learn. Sci. Tech.* **1** (2020) 035012, [1912.12238]. 11

[1851] R. Sahoo, S. Prasad, N. Mallick, K. Goswami and G. B. Mohanty, *Prompt and non-prompt production of charm hadrons in proton-proton collisions at the Large*

Hadron Collider using machine learning, vol. 4, p. 100085, 4, 2025. 2504.09541. DOI. 11

[1852] J. Li and H. Sun, *Learnable cut flow*, 2503.22498.

[1853] CMS Collaboration, *Inclusive search for highly boosted Higgs bosons decaying to bottom quark-antiquark pairs in proton-proton collisions at $\sqrt{s} =$ 13 TeV*, *JHEP* **12** (2020) 085, [2006.13251].

[1854] ATLAS Collaboration, *Search for Higgs boson decays into a Z boson and a light hadronically decaying resonance using 13 TeV pp collision data from the ATLAS detector*, 2004.01678.

[1855] ATLAS Collaboration, *Search for non-resonant Higgs boson pair production in the $bb\ell\nu\ell\nu$ final state with the ATLAS detector in pp collisions at $\sqrt{s} = 13$ TeV*, *Phys. Lett. B* **801** (2020) 135145, [1908.06765]. 11

[1856] H1 Collaboration, *Unbinned Deep Learning Jet Substructure Measurement in High Q^2 ep collisions at HERA*, *Phys.Lett.B* **844** (3, 2023) 138101, [2303.13620]. 11