

Artificial Intelligence in Modern Physics Research: Applications, Challenges, and Future Directions

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Abstract: Recent years have seen a paradigm shift in physics from analytical and theory-driven approach to data-driven technology. The reason behind this transformation lies in the exponential growth in experimental and simulation data generated in various fields of physics. Owing to explosion of heterogeneous and high-dimensional data, Artificial Intelligence based techniques have become backbone of research in modern physics to facilitate data analysis, complex problem solving and experimental design. This paper provides a comprehensive discussion on the applications of machine learning across different domains of physics including quantum physics, astrophysics, high-energy physics, condensed matter physics, plasma physics and nuclear physics. This manuscript explores various machine learning and deep learning-based approaches such as Graph Neural Network, Physics-Informed Neural Networks, Generative adversarial models etc. in uncovering features of complex physics systems. The paper outlines the challenges in amalgamation of AI methods with traditional physics frameworks. The discussion also investigates the future possibilities in reshaping field of physics with advancement in AI.

Keywords: Artificial Intelligence; Machine Learning; Deep Learning; Physics-Informed Neural Networks; Graph Neural Networks; AI in Physics

1. Introduction

AI methodologies and modelling tools have showcased their potential in processing of large-scale data and providing powerful solution across many domains [1]. Physics relates to natural science that deals with the study of various fundamental concepts like matter, space, energy, time etc in terms of their properties and interaction. Traditional physics methodologies were based on theory-driven models from Newtonian based concepts of motion to quantum base concepts of atoms. But past decade has witnessed a paradigm shift from analytic theory to data-driven discovery in physics. The advancement in experimental facilities and simulations have generated huge amount of complex data for instance, petabytes of collision events are captured by particle colliders, high-dimensional state data is recorded by quantum simulators and millions of compounds are contained in a materials database. This enormous volume of complex and high-dimensional data is difficult to analyze manually and requires amalgamation of computational approaches for processing the available plethora of data [2]. Addressing the aforementioned challenges, physics research is increasingly intertwined with advances in artificial intelligence (AI). Machine learning (ML), deep neural networks, and related AI tools can analyze complex data and learn patterns with high speed and accuracy far beyond traditional code. AI techniques facilitate system modelling, extraction of signals from noise, and even guidance during experiments. In physics research, ML is adopted to accelerates different aspects from recognizing new particles to exploring novel materials. This amalgamation of AI for effective modelling of complex data has resulted in evolution in physics, moving from data to discovery. In various endeavors AI models are implemented to discover new forms of physics research that go beyond analytical solvability, for instance, Degraeve et al. [3] implemented reinforcement learning based framework to control plasma configurations in fusion reactors autonomously, Dan et al. [4] employed generative model to design materials with specified electronic properties. Similarly, Raissi et al. [5] used a hybrid framework comprising physics-informed neural network embedding AI for solving non-linear partial differential equations based forward and inverse problems. The integration of AI with physics fosters scalability as well as exploration in the domain of natural science. Managing of large and complex data from experiments like James Webb Space Telescope observations or Large Hadron Collider (LHC) highlights scalability of AI-enabled hybrid approaches. Exploration is promoted by allowing the AI-based models in discovering areas like quantum entanglement, where theory is insufficient.

This study aims to review the various AI technologies employed in physics research for improving simulations and experiments. The AI-driven research in physics is categorized across six major areas – Quantum physics, astrophysics, high-energy physics, condensed matter physics, plasma physics and nuclear physics. Various case studies are discussed to get insight about hybrid AI-physics approaches. The paper also outlines various issues and future possibilities related to AI-enabled discoveries in physics. The following sections of the manuscript provide synthesis and comparative analysis of representative studies in diverse areas of physics.

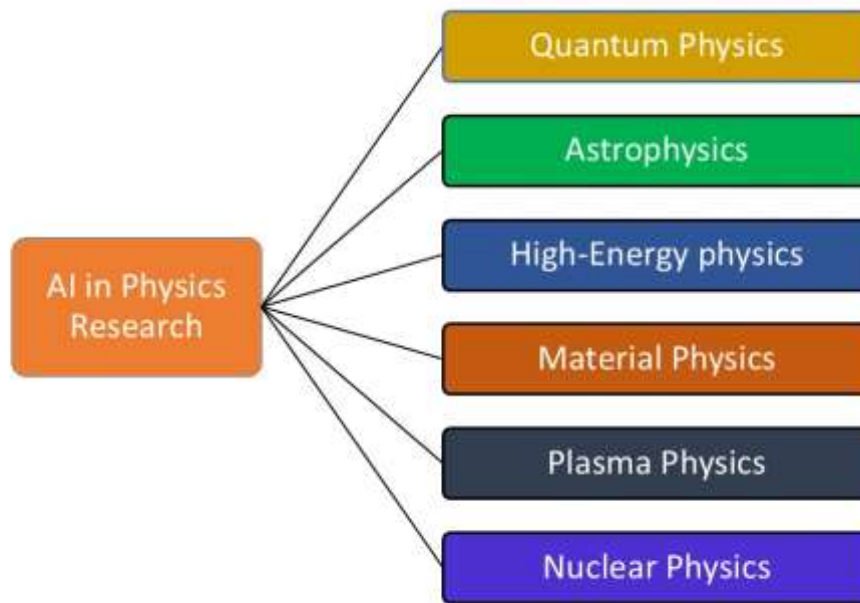


Fig. 1: Applications of AI across various domains of physics

2. AI in different domains of physics

The section discusses the various approaches combining AI mechanism across various domain of physics including Quantum physics, astrophysics, high-energy physics, condensed matter physics, plasma physics and nuclear physics, as depicted in Fig. 1.

2.1 AI in Quantum Physics

Quantum physics relates to the study of phenomena at the atomic and subatomic scales. The main challenge of quantum physics lies in the highly complex nature of quantum many-body systems. The traditional computational methods like density matrix renormalization group (DMRG) fail to scale for large systems. AI techniques came into rescue for quantum state representations with promising performance. Carleo et al [6] introduced the restricted Boltzmann machines (RBMs) based Neural Network Quantum States (NNQS) for approximation of wave functions. This work used a neural network to encode highly entangled quantum systems, which are computationally infeasible to implement using traditional computations. Convolutional neural networks (CNNs) based models are employed to identify and correct qubit errors in surface codes [7]. Reinforcement learning (RL) methodology is adopted in research related to quantum control problems. Bukov et al. (2018) implemented RL agents for designing control protocols to generate quantum state [8]. Olle et al. [13] employed deep RL to develop noise-aware quantum error-correcting codes robust to data noises. Pfau et al. [9] introduced a deep neural network, *FermiNet*, that supports antisymmetric, to generate ab initio solutions for many-electron equations. Further, Torlai et al.[10] used generative adversarial networks (GANs) to reconstruct quantum states from experimental data in quantum theory. The various studies integrating AI in the area of quantum physics are listed in Table 1, specifying the AI model employed, dataset used and remarks about study.

Table 1: Comparative Analysis of Studies on AI Applications in Quantum Physics

Study	Task	AI Model Used	Dataset Detail	Remarks
Carleo et al. [6]	simulate dynamics	Neural-network quantum states (NNQS)	Simulated spin models- 1D/2D Heisenberg	Introduced NNQS; High accuracy

Krastanov et al. [7]	Quantum error correction	Deep neural network probabilistic decoder	Stabilizer codes simulations	Improved decoding accuracy
Bukov et al. [8]	Quantum Code optimization	Reinforcement Learning	Simulated Quantum Control Data	Improved decoding accuracy
Pfau et al [9]	Solving many-electron Schrodinger equation	Deep neural networks (FermiNet)	Ab initio quantum datasets	High-accuracy solutions to electronic structure
Torlai et al. [10]	State tomography	Neural density estimators	Simulations & small experimental data	Improvement over NNQS; Efficient state reconstruction; benchmarks on small systems
Wu et al. (NNQS-Transformer) [11]	Electronic structure estimation	Transformer-based NNQS	electronic structure data	Improved scalability; better sampling
Li et al. (RLfD) [12]	Control pulse optimization for gates	Reinforcement Learning	Superconducting qubit simulations and pulse datasets	Faster convergence; high efficiency, robust approach
Olle et al. [13]	optimize quantum error-correcting codes	Deep RL (noise-aware) for Quantum Error Correct(QEC) code search	Simulated noisy quantum devices	Explored hardware-tailored codes; robust against noise
Zhang et al. [14]	Ground-state energies for fermionic systems	Variational Monte Carlo + neural-network	Many-body fermionic simulations	Improved variational energies
Macaluso et al. [15]	Efficient sampling of many-body distributions	Neural Monte Carlo samplers	Lattice model datasets	Efficient sampling, reduced autocorrelation
Zhang et al.[16]	Quantum dynamics prediction	Long Short Term Memory (LSTM)	Simulated time evolution data	Useful for quantum simulation and forecasting; modelled long-term quantum dynamics

The AI embedded models showcased better performance in state representations, phase recognition, tomography and extraction of hidden symmetries in quantum systems. But the inherent nature of neural network makes training of model for quantum systems a computationally expensive task with interpretability issue.

2.2 AI in Astrophysics

Astrophysics include analysis of large-scale astronomical data obtained through observations, surveys and high-fidelity simulations and satellite data. AI techniques have shown remarkable performance in processing of astronomical images, analyzing time-series data, and performing cosmological simulations[17-26]. Shallue et al.[17] introduced the use of convolutional neural networks (CNNs) for analysis of Kepler light curves. ExoMiner[18] employed explainable CNNs to Kepler and TESS datasets and resulted in validation of 301 new exoplanets with high accuracy. Scientific transparency is of utmost importance in astrophysics, highlighting the importance of explainability in underlying model. Machine learning concepts have also showcased their effectiveness in transforming the field of Gravitational-wave (GW) astronomy. Tian et al. [19] implemented CNN-based feature extraction followed by Random Forest-based classification of GW signals in LIGO data, resulting in high performance and robustness to noise on input. Machine learning based model have grasped the attention on researcher in the area of galaxy evolution in investigation of stellar

mass, star formation rate, and photometric data analysis for metal estimation. Zeraatgari et al. [20] proposed a random forest and neural networks-based framework for prediction of mass and star formation rates. Autoencoders based model is adopted by Bohm et al.[21] for identification of anomalous galaxies. ML-based emulators fostered the research in cosmology for the analysis of cosmological data in an efficient manner. Kannan et al.[22] proposed CosmoFlow - a flow-based model to compress large-scale cosmological data into low-dimensional latent spaces. The use of reduced dimension features resulted in an efficient parameter inference and uncertainty quantification. Kreisch et al. [23] implemented a Graph Neural network (GNN) based model for estimation of cosmological parameters from sparse point distributions through clustering of galaxy data. Strong lensing detection is another successful example of integration of ML and astrophysics. Petrillo et al. [24] proposed a U-Net based architecture for recognition of lensing candidates in surveys like HSC and DES with high accuracy and low inference time. Finke et al.[25] deployed an RNN based model for classification of weak pulsar signals from noisy time-series data. Ho et al.[26] proposed an implicit likelihood-based inference framework for analyzing various properties related to astrophysics such as identification of galaxy cluster masses, estimating progenitors in gravitational wave signals and capturing physical dust parameters from galaxy images. Despite the growing research in AI-based hybrid approaches, data heterogeneity across surveys and satellite data makes the ML model to suffer with domain shift and limiting generalization. The black box behavior of the model hampers the interpretability. The various studies merging AI in Astrophysics are presented in Table 2.

Table 2: Comparative Analysis of Studies on AI Applications in Astrophysics

Study	Task	AI Model	Dataset	Key Remarks
Shallue & Vanderburg [17]	Exoplanet detection	CNN	Kepler light curves	Automated feature learning and successful discovery of planets; telescope-specific training limits generalization.
Valizadegan et al. [18]	Exoplanet validation	ExoMiner deep neural network	Kepler candidates	Highly accurate and explainable; strong dependence on Kepler-derived data.
Tian et al. [19]	GW feature learning	CNN + Random Forest	GW signal/noise data	Combines deep feature extraction with interpretability; hybrid complexity.
Zeraatgari et al. [20]	Galactic-property prediction	ML regression	Photometric galaxy data	Enables large-scale estimation of physical properties; affected by photometric uncertainties.
Böhm et al. [21]	Anomalous galaxy detection	Neural Density Estimation	Galaxy spectra	Detects rare/unseen anomalies without exhaustive labels; physical interpretation remains challenging.
Kannan et al. [22]	Cosmological representation learning	Flow matching	Cosmological simulations/data	Scale-aware representation learning; computational and observational-generalization challenges.
Kreisch et al. [23]	Precision cosmology	ML + void statistics	GIGANTES simulations	Large-scale benchmark for ML cosmology; simulation-to-observation gap.
Petrillo et al. [24]	Strong-lens detection	CNN	KiDS survey images	Effective automated visual classification; sensitive to training-data realism.
Finke et al. [25]	Pulsar/source classification	RNN	Fermi-LAT energy/time spectra	Exploits temporal information and is particularly relevant to pulsar classification; not specifically focused on weak radio pulsar signals.
Ho et al. [26]	Astrophysical inference	LtU-ILI / implicit inference		Flexible general framework; not specialized for a particular astronomical classification task.

2.3 AI in High-Energy Physics (HEP)

High Energy Physics deals with study of processes happening at very small scales but with very high energies. It explores elementary particles such as quarks, leptons, and bosons, along with their weak, strong and electromagnetic interactions. High-energy physics

(HEP) experiments, such as at Large Hadron Collider (LHC), generate huge amount of data annually. It is infeasible for the traditional methods to filter, and analyze this massive data. To address these challenges, AI techniques have emerged as effective tool for processing of experimental data for event reconstruction, particle tracking and anomaly detection with high accuracy and efficiency [27][28]. Baldi et al. proposed a boosted decision trees and deep neural networks (DNN) based model to detect signal with remarkable accuracy [29].

Another usage of AI in HEP is in implementation of trigger systems which make decision about recording of an event in real time. Clerbaux et al. [30] employed a Multi-Layer Perceptron (MLP) model to enhance trigger efficiency while mitigating false alarms. The main consideration of a trigger system is its latency which should be know enough to make decision at ultra-high speed. To reduce the latency in FPGA trigger system, compression and quantization techniques are adopted in neural network [31]. Inclusion of AI has also transformed multiple areas of HEP including Particle tracking, jet tagging and simulations. Shlomi et al. [32] implemented a GNN based model for reconstruction of complex particle trajectories in high-density environments. Exploiting the graph structure, a GNN based model is developed for b-jet tagging[33].

In simulation, generative adversarial networks (GANs) based framework are designed to normalize the flows during emulation of calorimeter showers with low computational costs with comparable fidelity [34][35][36]. CNN and GNN based end-to-end model have showcased their efficacy in classification of detector-level data, without computing hand-crafted features. Komiske et al. [37] implemented an end-to-end deep model for binary classification of jets into quark and gluon jets. Machine learning approaches are also adopted for unsupervised anomaly detection for Beyond Standard Model (BSM) searches. Heimel et al. [38] employed an autoencoder-based architecture to identify the unusual event in distribution.

Table 3: Comparative Analysis of Studies on AI Applications in High-Energy Physics (HEP)

Study	Technique Used	AI Model Used	Dataset Detail	Remarks
Radovic et al. [27]	Supervised & unsupervised ML for classification & anomaly detection	Boosted decision trees, deep neural networks	LHC datasets (ATLAS, CMS)	Landmark review showing ML at forefront of particle physics; improved event classification & trigger efficiency
Adam-Bourdarios et al. [28]	Classification challenge (signal vs. background)	Ensemble ML models (GBDTs, DNNs)	Simulated Higgs boson events	Open competition dataset; catalyzed global progress in HEP ML
Baldi et al. [29]	Exotic particle search	Deep feedforward neural networks	Simulated LHC collision events	Demonstrated DNNs outperform manual feature engineering
Clerbaux et al. [30] - JUNO experiment	Trigger decision optimization	ML classifiers (NNs, decision trees)	JUNO detector simulation	ML-based trigger reduced latency, improved detection of low-energy neutrinos
Fahim et al. [31] HLS4ML	Real-time inference optimization	Compressed DNNs on FPGA	CMS open data & HL-LHC simulations	Achieved ultra-low latency inference ($<1 \mu s$) for triggers
Shlomi et al. [32]	Relational reasoning for jets/particles	Graph Neural Networks (GNNs)	LHC jet physics datasets	Introduced GNNs as natural fit for particle interactions

Duperrin et al. [33]	Jet flavor tagging	Graph Neural Networks	ATLAS Run-2 dataset	GNN-based b-tagging significantly improved over standard DL
Paganini et al. [34]- CaloGAN	Fast detector simulation	Generative Adversarial Networks (GANs)	ATLAS calorimeter simulation data	GANs 1000x faster than GEANT4 with good accuracy
Krause & Shih [35]- CaloFlow	Calorimeter simulation	Normalizing Flows	ATLAS calorimeter data	Flows gave improved likelihood-based calibration
Howard et al. [36]- iCaloFlow	Iterative calorimeter shower simulation	Iterative Normalizing Flows	ATLAS calorimeter datasets	Reduced mode collapse, improved fidelity over CaloFlow
Komiske et al. [37]	Jet substructure learning	Deep Sets / Energy Flow Networks	LHC jet datasets	Permutation-invariant networks showed strong jet classification
Heimel et al. [38] -	Rare event detection	Autoencoders	LHC simulated collider data	Identified new physics signals without supervision

2.4 Condensed Matter & Materials Physics

Condensed matter and material physics deals with study of materials and many-body quantum systems. This domain of physics has historically relied on statistical mechanics, quantum theory, and experimental characterization to explore the properties of materials. The modern material like topological insulators, increased the complexity in the field and resulted in large datasets (from ab initio simulations, materials databases, or quantum microscopes). To address the added challenges and to obtain insights from large collection of observations and experiments, AI techniques are adopted in the field to predict material properties and discover new phases with higher accuracy. The various field specific computational approaches like density functional theory (DFT), molecular dynamics etc are complemented with ML approaches. This amalgamation enables pattern discovery in large simulation datasets, facilitates material property prediction, and aids in the inverse design of novel compounds.

Deep neural networks enable accurate predictions of ground-state energies or magnetic order by effectively learning effective Hamiltonians of complex quantum materials directly from experimental data [39]. Carleo and Troyer [6] introduced a scalable neural-network quantum states (NNQS) employing restricted Boltzmann machines for effective representation of wave functions of interacting quantum systems. Pfau et al. [9] extended the work by using convolutional neural networks and variational autoencoders for providing accurate ground-state energies for strongly correlated systems with reduced complexity.

Under Condensed Matter & Materials Physics, AI-driven frameworks accelerated the materials discovery. Xie et al. [40] leveraged Open Quantum Materials Database (OQMD) of DFT-calculated material properties for training of ML models for rapid prediction of band gaps, elastic moduli, and thermodynamic stability. Chen et al. [41] adopted a Graph neural network (GNNs) based Crystal Graph Convolutional Neural Network (CGCNN) for encoding of structural and chemical features of crystals.

Further exploring the effect of unsupervised learning, Kusne et al. [42] proposed a reinforcement learning based Bayesian optimization to assist thin-film synthesis. This closed-loop system resulted in a reduced set of physical experiments for discovering optimal compositions. Dan et al. [4] introduced a generative adversarial network (GANs) based framework for designing inverse material and creating candidate structures supporting specified electronic properties.

Table 4: Comparative Analysis of Studies on AI Applications in Materials Physics

Study	Task	AI Model Used	Dataset Detail	Remarks
Carleo et al. [6]	Solve quantum many-body Schrödinger equation	Restricted Boltzmann Machine (RBM)	Simulated data from quantum spin system	-Achieved ground-state energy estimates comparable to traditional Quantum Monte Carlo methods -Suffers with Scalability issues
Pfau et al. [9]	Ab initio solution of many-electron Schrödinger equation	Fermionic Neural Network (FermiNet)	Quantum chemical benchmark datasets	- Outperformed conventional Variational Monte Carlo accuracy - Computationally expensive; scalability to large atoms/molecules limited.
Xie et al. [40]	Predict material properties	Crystal Graph Convolutional Neural Network (CGCNN)	Materials Project database	- Achieved high prediction accuracy -Requires sufficient labeled data; limited to crystalline structures.
Chen et al. [41]	Prediction of both molecular and crystal properties	Graph Neural Network (MEGNet — Materials Graph Network)	Materials Project	- Achieved mean absolute errors < 0.05 eV for formation energy -Less efficient for amorphous or non-periodic materials.
Kusne et al. [42]	Autonomous materials discovery	Bayesian Learning with Gaussian Processes	Experimental dataset from high-throughput material synthesis	-Real-time closed-loop optimization of experiments. - Discovered new materials with reduced number of experiments -Performance depends on initial training data; model retraining needed for new domains.
Dan et al. [4]	Inverse design of inorganic materials — generate new stable structures	Generative Adversarial Network (GAN)	Computational datasets of inorganic crystal structures	-First use of GANs for inverse materials design. - Successfully generated valid and stable inorganic compounds (stability >85%) -Mode collapse risk and limited interpretability of generated structures.

The performance of AI based approaches is limited by data availability in material study. Though transfer learning and active learning approaches have emerged to address data scarcity but large-scale annotated datasets are still critical. Despite of aforesaid challenge, the prediction of material behavior and designing of novel quantum materials have accelerated with the inclusion of AI in condensed matter physics.

2.5 AI in Plasma Physics

Plasma physics deals with processes including fusion energy, space plasmas, and industrial plasmas. Its applications spans from controlled nuclear fusion to astrophysical plasmas and require modeling of turbulent, nonlinear, and multi-scale systems. Most plasma data (experimental, observational, computational) are generated by machines and thus their processing is computationally demanding. The traditional methods like magnetohydrodynamic (MHD) simulations are not able to capture the full dynamics of turbulent plasmas. To address the aforesaid limitation of fast and accurate processing of plasma data, AI approaches have emerged as effective and efficient data-driven methods [43]. Kates-Harbeck et al. [44] introduces deep-learning based Disruption Prediction (DELPHI) employing a recurrent neural network (RNN) for real-time control and prediction of plasma disruption from plethora of

diagnostic data, tokamak, *obtained through multiple devices* (including DIII-D, JET tokamaks, Alcator C-Mod, EAST). DELPHI outperformed previous heuristic-based methods highlighting the successful integration of AI in heterogeneous plasma diagnostics for real-time prediction. Seo et al. [48] demonstrated an AI trained controller that sustained tearing likelihood below a threshold in real DIII-D experiments and exhibited robust behavior under challenging conditions like low safety factor, low torque.

Surrogate modeling is another subfield of plasma physics where emergence of AI facilitated low-cost approximation of turbulence simulations. Montes et al. [45] used convolutional networks for prediction of energy transport fluxes from gyrokinetic turbulence simulation data. These AI-assisted surrogate models resulted in tens to hundreds of times faster parameter scans and uncertainty quantification. Jin et al. [46] leveraged physics-informed neural networks (PINNs) to plasma wave propagation and MHD equilibrium problems and obtained high accuracy under embedded physical constraints. Recently, GyroSwin et al. [47] approach enabled orders-of-magnitude speedups for gyrokinetic simulations by transforming low-dim surrogates into 5D generative/transformer surrogates for optimizing the design and control mechanism in modeling.

AI also emerged as crucial tool for designing of control systems for plasma confinement. Degraeve et al [3] proposed a Reinforcement learning (RL) based model to optimize the control system in terms of heating, current drive, and magnetic field configurations to sustain stable plasmas. The developed RL model successfully applied on real-time tokamak plasma shape control, marking a breakthrough in AI-driven fusion research.

Despite the adoption of AI in plasma physics concepts, the stochastic nature of plasma presents challenges for ML models. The generated data is noisy or limited due to the cost of experiment setups. Another issue is related to transferability of ML model due to lack of cross-device generalization. The subfield requires focus on different aspects of AI concepts like federated learning, uncertainty-aware models for robust deployment in next-generation reactors.

Table 5: Comparative Analysis of Studies on AI Applications in Plasma Physics

Study (Year)	Task	AI Model	Dataset Detail	Remarks
Kates-Harbeck et al. [44]	Predict disruptive plasma instabilities before they occur	Deep Learning - Convolutional LSTM (Long Short-Term Memory) architecture integrating plasma diagnostic time series	Experimental data from the DIII-D tokamak	First Achieved high accuracy in prediction -Improved reliability -Model generalization is uncertain.
Montes et al., 2021 [45]	Develop fast surrogate models for nonlinear gyrokinetic turbulence simulations	Machine Learning - based model using Gaussian Process Regression (GPR) and Feedforward Neural Networks (FNNs)	Synthetic data generated from gyrokinetic turbulence simulations (using GENE code)	Achieved high-speed-up while maintaining good accuracy in reproducing energy flux spectra -Trained on limited parameter space
Jin et al., 2021 [46]	Solve magnetohydrodynamic (MHD) PDEs directly using data-driven learning	Physics-Informed Neural Networks (PINNs)	Simulated data for 2D and 3D MHD problems;	-Unified data- and physics-driven modeling without labeled data. -accurate reconstruction of velocity, pressure, and magnetic fields - High Training cost

				-Limited scalability to high-dimensional MHD systems
Degrave et al., 2022 [3]	Achieve real-time magnetic control of plasma shape & position	Deep Reinforcement Learning (DRL) using Actor-Critic architecture with real-time control loops	Experimental & simulated data from TCV tokamak (Switzerland); plasma shape & magnetic data	- First endeavor of DRL in closed-loop plasma control. - Successfully stabilized and shaped unseen plasma configurations - Requires extensive simulation training
Seo et al., 2024 [48]	Reduce probability of disruptive tearing instabilities via learned controllers	Deep learning controller (RL/ML hybrid)	Experimental data & control experiments on the DIII-D tokamak	- First demonstration of AI lowering tearing-instability risk on tokamak. - Suffers with scalability and robustness issues

2.6 AI in Nuclear Physics

In nuclear physics, AI has transformed research practices across various subfields ranging from low-energy nuclear structure to high-energy nuclear collisions. ML models are employed to predict nuclear characteristics like masses, decay rates, spectra as well as to optimize complex simulations of nuclear matter. ML acts as an effective and crucial tool to interpret vast datasets from particle accelerators and nuclear reactors and for anomaly detection in experimental data.

The most challenging aspect of research practices in nuclear structure physics is predicting binding energies and nuclear masses. Niu et al. [49] proposed a Bayesian neural network (BNN) to predict nuclear masses. The proposed model outperformed semi-empirical models in point estimates for masses and reliable posterior uncertainty estimates for extrapolations. Gao et al. [50] introduced LightGBM using gradient boosting to refine global mass models and to predict unseen masses. SHAP explainability is applied to interpret feature importance. Dong et al. [51] designed a refined Bayesian neural network architecture to improve rms deviation and deliver robust uncertainty estimates through training of model on charge radii with physics-informed engineered inputs.

Utama et al. [52] combined support vector machines (SVMs) with radial basis kernel for improved mass predictions. Neufcourt et al. [53] employed Bayesian statistical emulators, combining gaussian process and BNN, for a reliable extrapolation of nuclear masses with quantified uncertainties. Ma et al. [54] used ML model to predict neutron capture cross-sections, a critical quantity in nuclear astrophysics and reactor design. Yuksel et al. [55] used ML regressors (Support Vector Regression, Gaussian Process Regression) integrated with physics-informed feature engineering to predict nuclear mass excesses. Lu et al. [56] used a CNN based architecture capturing both global features along with local nuclear-chart neighborhood features to predict mass residuals.

In the experimental domain, AI simplifies event reconstruction and anomaly detection. Paganini et al. [34] developed CaloGAN, a Generative Adversarial Network (GAN), to simulate calorimeter showers in high-energy nuclear experiments. The framework facilitated ultra-fast approximate simulation for detector studies and high-statistics analysis.

Hybrid approaches integrating nuclear physics symmetries into neural networks as well as probabilistic ML methods, are promising directions. The challenges need to address for successful implementation of AI in nuclear physics applications include sparse experimental data and uncertainty quantification. Interpretability is another critical issue as predictions must align with established nuclear models and constraints.

Table 6: Comparative Analysis of Studies on AI Applications in Nuclear Physics

Study	Task	AI Technique	Dataset	Remarks
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Ma et al. [54]	Predict neutron-capture cross sections where data are sparse.	ML regressors	Experimental & evaluated neutron-capture datasets	-Predicted cross sections with reduced errors -Produces fast surrogate estimates for nucleosynthesis
Neufcourt et al. [53]	Model-based extrapolation and uncertainty quantification	Bayesian emulators: Gaussian processes, Bayesian neural networks (BNN)	Residuals between global nuclear models and experimental masses (AME database)	-Significant RMS reduction vs raw models -robust and improved predictive power -Emphasis on honest uncertainty quantification
Niu & Liang [49]	Improve mass predictions, provide uncertainties	BNN	Experimental masses + theoretical mass model residuals	-Smaller rms errors vs baseline models - uncertainty estimates for extrapolations
Paganini et al. [34]	Fast emulation of 3D calorimeter showers	Generative Adversarial Networks (CaloGAN)	Full Geant4 calorimeter simulation datasets (electromagnetic showers)	-Fast with good visual/metric fidelity -first attempt towards generative simulation; -suffers with local artifacts possible.
Utama et al. [52]	global predictions of masses & uncertainties	Bayesian Neural Network (BNN) + DFT inputs	DFT model outputs + experimental masses radii	-Reduced rms deviations -Improved charge-radius predictions -Combines physics (DFT) with BNN residual learning
Gao et al. [50]	Refine theoretical mass models; predict unknown masses	LightGBM (gradient boosting), SHAP explainability	Experimental mass evaluations (AME) + features	- RMS improvements vs baseline models - Interpretable feature importances
Yuksel et al. [55]	Predict nuclear mass excess; assess extrapolation	SVR, Gaussian Process Regression (GPR)	Experimental masses (AME2020) + physics features	- Competitive accuracy; - GPR provides uncertainty bands - Emphasizes extrapolation tests.
Dong et al. [51]	Predict nuclear charge radii with uncertainties	Refined BNN	Charge radius datasets	-Reduced RMS -Good extrapolation behavior -Reliable uncertainty quantification
Lu et al. [56]	Nuclear mass prediction using local context + global model	Convolutional Neural Network (CNN) + hybrid global-local scheme	Experimental masses + neighboring nuclei features + theoretical model residuals	-Improved mass predictions -Combines local neighborhood (CNN) with global physics model

3. Analysis of integration of AI in Physics domain

This section of the analyzes the benefits of the augmentation of physics concept with AI and the various challenges and the limitation of this integration.

3.1 Role and Benefits of AI in Physics-Based Modeling

The integration of AI with physics-based approaches offers several advantages in scientific research and engineering applications. By combining the computational capabilities of AI with the established principles of physics, these approaches can improve

computational efficiency, prediction accuracy, data handling, and the interpretation of complex physical phenomena. The major benefits of this integration are discussed below.

- **Speed and Efficiency:** AI models' intrinsic nature allows them to evaluate complex models at faster pace compared to conventional solvers. A neural network trained on existing simulation results is able to produce near-instant prediction of new case. This behavior of AI models results in shorter design cycles in engineering and quicker turnaround in data analysis.
- **Improved Accuracy:** AI methods have improved the precision of prediction showcasing their ability in capturing subtle non-linear effects that coarse analytic models may miss. Blending ML with physics constraints yielded more accurate and interpretable distributions than standard fits. In detection tasks, deep networks can extract faint signals from noisy data with higher fidelity than simpler filters.
- **Scalability with Big Data:** Modern physics experiments produce volumetric datasets at the rate of petabytes per run. This huge data is very difficult to handle through manual analysis. AI architecture exhibit scalability across such data volumes. This allows discoveries from patterns hidden in high-dimensional observations in real time.
- **Automated Hypothesis Generation:** AI architectures are found to observe patterns or models that cannot be anticipated manually. This will allow research practices in proposing novel descriptions or symmetries in complex phenomena. Though AI generated predictions require human interpretation, it can guide researchers toward overlooked relationships.
- **Bridging Theory and Experiment:** Hybrid methods can provide tight coupling between theory and data by fusing ML concepts with traditional physics knowledge. The physics-informed networks ensure models follow conservation laws, while generative AI can integrate sparse experimental data with theoretical priors. These collaborations result in robust analysis and simulations.

3.2 Issues regarding integration of AI in Physics domain

The interesting synthesis of modern age AI and traditional physics come with important limitations and caveats:

- **Data Quality and Bias:** The goodness of ML model largely depends upon the quality of training data. The sparse, noisy, or biased data hampers the performance of AI model. As the data obtained through experimental setup is of poor quality, the AI model fails to achieve to maximum of its potential.
- **Reproducibility Issue:** AI driven science suffers with "reproducibility crisis" owing to data leakage causing overoptimistic results. Some early attempts (like PINN) failed to solve new problems [57].
- **Interpretability Issue: ("Black Box"):** Deep neural networks act as black box as it is difficult to interpret the behavior of AI model in giving a prediction. It is very challenging to represent physical insight directly from a trained model. In modern physics research experiments AI is treated as an output tool rather than explanations. This lack of transparency requires to validate AI results carefully against known physics. Though ML models are capable of predicting novel theories but verification of automatically generated concepts is must to ensure it isn't an artifact of training data.
- **Generalization and Extrapolation:** AI excels the prediction accuracy within the range of training data but the performance degrades drastically for unseen observation. ML model trained on a specific set of materials will be able to predict certain characteristic of a different alloy outside the training domain. This restricts the application of AI model designed for one range for extrapolation to beyond the proven range.
- **Computational Resources:** The implementation of AI techniques is computationally expensive exercise. Applying AI in real-time experiments requires fast and costly hardware like GPUs, FPGAs etc. This high-end resource requirement causes the high cost in realization of hybrid architectures.

Adoption of AI to physics research brings great power but this integration needs proper calibration and interpretation. The AI techniques augment human analysis but cannot yet replace the requirement of sound physical reasoning.

4. Future Possibilities: Toward New Discoveries

The future aspects of hybrid approaches may include interesting ventures. The future research may span from autonomous experimentation, exponential speeding up of processes and innovative Human-AI collaborations.

Autonomous Laboratories: The successful synthesis of AI in physics experiments may result in fully automated labs. AI assisted designing of experiments will be carried out on the fly. For instance, an AI-assisted quantum optics lab can leverage ML techniques to adjust mirror positions or laser frequencies in real time without human intervention [58].

New Physical Laws and Theories via AI: The applications of AI-driven symbolic and sparse-regression methods can be extended to extract new laws directly from experimental and simulated data. Future workflows may include neural networks as high-capacity function approximators with symbolic modules and sparsity priors to discover human-interpretable candidate laws along with uncertainty estimates. This can simplify the transformation process of data to governing equations in complex and noisy systems. AI techniques can be used to formalize emergent phenomena discovered in high-dimensional experiments [59].

Quantum Computing Meets AI: The intersection of quantum computing and AI can be used to extend two related sub-fields : *quantum-enhanced ML* and *ML-assisted quantum algorithms and control*. Under quantum-enhanced ML, near-term quantum can be used to improve learning for quantum-native tasks particularly state tomography, simulation, materials design. The *ML-assisted quantum algorithms and control* may employ classical ML to design quantum circuits and control qubits more robustly. The future of amalgamation of ML and quantum computing will include development of hybrid quantum-classical toolchains where ML proposes compresses quantum states resulting practical gains for quantum many-body problems [58].

Large-Scale Data Synthesis and Sharing: Existing AI-based models like scaling NNQS [6] can be scaled to larger systems. Hybrid quantum-classical or variational algorithms can be developed that use ML techniques as variational circuits, uncertainty-aware ML for critical properties, integrating with tensor-network and quantum-hardware emulation for real experiments.

Use of federation learning: Federated learning approaches might be applied to collaboratively refine a global model at different labs while keeping proprietary data private.

Human-AI Collaboration: AI concepts will act as a collaborator to amplify insights to physicists. The human domain expertise with AI's strengths will result in the most productive workflows. Future lab workflows may include AI co-pilots that propose hypotheses, design next experiments, highlight anomalies, and draft mathematical conjectures but the final judgment, interpretability checks and assessment of conceptual frameworks are carried out by human.

The convergence of AI with quantum computing, autonomous laboratories, and large-scale data infrastructures promises speed in discovery and theory formation. The hybrid approaches will lead to conceptual innovation and validation and will accelerate the pace at which new physical laws, materials, and technologies emerge.

5. Conclusion

AI is rapidly transforming physics from observational and simulation-driven science to adaptive, data-centric, and autonomous field.

ML models and neural networks augment traditional methods by addressing complexity, accelerating computations and discovering hidden structures in data. The AI-driven frameworks have improved accuracy, scalability and speed of workflow across diverse domains ranging from quantum systems and astrophysics to high-energy, condensed matter, plasma, and nuclear physics. In quantum physics, NNQS, reinforcement learning, and generative model-based approaches enabled more accurate quantum state reconstruction, control protocols optimization, and reliable complex many-body systems implementation.

In astrophysics, AI models, particularly, convolutional neural networks (CNNs), graph neural networks (GNNs), and autoencoders, have facilitated the analysis of telescope and satellite data. ML algorithms showcased their effectiveness across varied tasks including identification of exoplanets and gravitational wave detection, galaxy classification and cosmological parameter estimation. These techniques enabled real-time data processing in large-scale surveys such as Kepler, TESS, and LIGO. In high-energy physics (HEP), the fusion of AI with experimental workflows drastically reduced simulation costs, enhanced event reconstruction, and improved particle tracking and jet tagging. The use of ML in real-time trigger systems has improved both latency and accuracy in event selection. In condensed matter and materials physics, ML models, including GNN, GAN and Reinforcement learning, Bayesian optimization frameworks, integrated with density functional theory (DFT) and molecular dynamics simulations have accelerated discovery of new materials with targeted properties. Similarly, AI has also revolutionized the prediction and control of plasma instabilities in fusion devices, in the domain of plasma physics. Deep learning frameworks provided real-time magnetic control of plasma shape, tearing instability mitigation and prediction of turbulence and energy transport. In nuclear physics, AI-driven models have significantly improved the prediction of nuclear masses, decay rates, and charge radii, outperforming conventional semi-empirical mass formulas. GAN-based simulators have accelerated detector simulations by several orders of magnitude. The hybrid approaches result in faster research and development cycles, more precise measurements and the ability to tackle complex problems. The study also discusses the benefits and challenges of the hybrid approach along with the future potential in the same direction.

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