Improvement of the Bayesian neural network to study the photoneutron yield cross sections (Postprint)

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Abstract

This work aims to improve the Bayesian neural network (BNN) for investigating photoneutron yield cross sections as functions of the charge number Z, mass number A, and incident energy. The BNN improvements focus on three aspects: numerical parameters, input layer, and network structure. First, numerical parameters—including the number of hidden layers, number of hidden nodes, and activation function—were optimized by minimizing deviations between predictions and experimental data. It was determined that a BNN architecture with three hidden layers, 10 hidden nodes, and a sigmoid activation function yielded the smallest deviations. Second, based on established physical knowledge such as isospin dependence and shape effects, optimal ground-state properties were selected as input neurons. Third, a Lorentzian function was employed to map hidden nodes to output cross sections, and an empirical formula for the Lorentzian parameters was utilized to connect certain input nodes to output cross sections. These latter two improvements enhanced prediction accuracy and mitigated overfitting, particularly for axially deformed nuclei.

Full Text

Preamble

Improvement of the Bayesian Neural Network to Study Photoneutron Yield Cross Sections

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This work presents an improved Bayesian neural network (BNN) for studying photoneutron yield cross sections as functions of charge number Z, mass number A, and incident energy . The BNN was enhanced in three aspects: numerical parameters, input layer design, and network architecture. First, by minimizing deviations between predictions and experimental data, we optimized numerical parameters including the number of hidden layers, number of hidden nodes, and activation function. The BNN with three hidden layers, 10 hidden nodes per layer, and sigmoid activation function yielded the smallest deviations. Second, based on established physical knowledge such as isospin dependence and shape effects, we selected optimal ground-state properties as input neurons. Third, we applied the Lorentzian function to map hidden nodes to output cross sections and used empirical formulas for Lorentzian parameters to link certain input nodes directly to outputs. These latter two improvements enhanced predictive accuracy and mitigated overfitting, particularly for axially deformed nuclei.

Keywords: Bayesian neural network, Photoneutron cross sections

Introduction

Neural networks are powerful predictive tools that have achieved remarkable success in nuclear physics over the past few years [?, ?, ?, ?, ?, ?]. The earliest application of neural networks to nuclear physics dates back to 1993, when a phenomenological approach based on multilayer feedforward networks was introduced to learn the systematics of atomic masses and nuclear spins and parities [?]. Since then, various neural network architectures have been applied to study nuclear mass systematics [?, ?], β-decay systematics [?], and binding energies [?].

Recently, incorporating physical ideas has further improved neural networks and unlocked their potential capabilities. Known physics has been explicitly embedded in Bayesian neural networks (BNNs), resulting in novel methods for accurately predicting β-decay half-lives [?]. Input data preprocessing that includes correlations among inputs reduces the problem of multiple solutions and yields more stable extrapolated results [?]. Combining a three-parameter formula with BNN has produced a novel approach for describing nuclear charge radii [?]. Additionally, neural networks can reveal physical laws; for example, a feedforward neural network trained to calculate nuclear charge radii suggested a correlation between symmetry energy and charge radii of Ca isotopes [?], while convolutional neural networks have been applied to determine impact parameters in heavy-ion collisions using constrained molecular dynamics simulations [?].

To date, neural networks have been widely used for signal identification [?, ?, ?], data restoration [?, ?], regression analysis [?], and numerous other applications throughout nuclear physics. In studies of nuclear masses and charge radii, Utama et al. demonstrated that physics-motivated models can provide initial predictions that BNNs subsequently refine by modeling residuals [?, ?]. This residual approach has improved predictions from several physics-motivated models in nuclear physics, including nuclear mass predictions from various models [?] and fission yield predictions using the TALYS model [?]. In studies of isotopic cross sections in proton-induced spallation reactions, BNN predictions learning experimental data directly were compared with those learning residuals from the SPACS parametrization [?], with the latter proving superior and highlighting the importance of robust physics-motivated models when using neural networks.

Neural networks are numerical algorithms, and in cases where physics-motivated models are unavailable, attempts have been made to provide physics guidance directly within the network architecture. A multitask neural network applied to learn giant dipole resonance parameters directly from experimental data produced better predictions than the Goldhaber-Teller model [?]. In studies determining impact parameters of heavy-ion collisions using convolutional neural networks, no initial predictions were made [?]. Beyond physics-motivated models, guidance can also be provided through the input layer [?] or via empirical formulas [?].

This study improves the BNN for studying photoneutron yield cross sections by incorporating enhancements to both the input layer and the output mapping through empirical formulas. Photonuclear reactions were first observed over 60 years ago [?], and their cross-section data are crucial for analyzing radiation transport, studying nuclear waste transmutation [?], and calculating nucleosynthesis rates [?, ?]. The underlying mechanisms in photonuclear reactions are significant for fundamental nuclear physics [?, ?]. The EXFOR database contains over 27,000 σxn data points for nuclei from ^{6}Li to ^{239}Pu at incident energies above the neutron separation energy [?], with new facilities continuing to produce additional measurements [?, ?]. This extensive dataset makes machine learning both feasible and advisable.

This paper focuses on improving the BNN for studying photoneutron yield cross sections. The remainder is organized as follows: Section II describes the model, Section III presents results and discussions, and Section IV provides a summary.

II. Model

The fundamentals of the BNN approach were established in the last century [?] and have become a standard method for pattern recognition and numerical regression, with the latter being our focus. In a standard BNN algorithm, a neural network with hidden layers maps inputs X to outputs Y:

Y (X,) = a + (cid:32) Nh(cid:88) (cid:88) (cid:33) djiXi

where   = {a, bj, cj, dji} are network parameters, {a, cj} are biases, and {bj, dji} are weights. The activation function f can be sigmoid, tanh, or softplus:

sigmoid(t) = 1 + exp(t) exp(t) − exp(−t) exp(t) + exp(−t) softplus(t) = log(1 + exp(t)). tanh(t) =

The activation function introduces nonlinearity between input and output.

The parameters in Eq. (1) are determined by learning from dataset D = $\{X^{(n)}$, $Y^{(n)}\}$ 1 , where Nd is the sample size. Bayesian theorem, which deduces posterior knowledge from prior distributions using likelihood functions, solves this regression problem. Specifically, assuming a prior distribution P( ) for parameters , the posterior distribution P(|D) given dataset D is:

P (|D) = P (D|)P ( ) (cid:82) P (D|)P ( )d

where P(D|) is the likelihood of D given .

With the posterior distribution of parameters , the expected output Ŷ* for known inputs X* is expressed as the integration:

(cid:90) Ŷ ∗ = Y (X ∗,)P (|D)d ,

Monte Carlo techniques evaluate this integration:

Ŷ ∗ = M CSP (|D) [Y (X ∗,)] Ns(cid:88) Y (X ∗, (k)),

where M CSP (|D) denotes Monte Carlo sampling from posterior distribution P(|D) and (k) (k = 1, 2, …, Ns) is the k-th sample drawn from P(|D) with total sample number Ns. The accuracy of Eq. (6) in evaluating Eq. (5) is:

Y ∗ = Ŷ ∗ ± 1.96

where S is the standard deviation of samples Y(X*, (k)). The difference between integration and Monte Carlo calculations can be reduced by increasing the sample number.

Analytic computation of posterior distribution P(|D) is intractable due to high parameter dimensionality. The BNN approach uses variational inference to approximate P(|D). Variational inference attempts to find such that q(|) minimizes the KL divergence from P(|D):

= arg min KL [q(|)||P (|D)] (cid:21) (cid:20) = arg min Eq(|) (cid:20) q(|) P (|D) q(|)P (D) P (D|)P ( ) (cid:2) ln q((k)|) − ln P ((k))(cid:21) = arg min Eq(|) = arg min (cid:88) − ln P (D| (k))(cid:3).

Traditional physics regression methods use empirical formulas with parameters, where appropriate formulas avoid misconvergence and overfitting. Similarly, when applying BNNs in physics, selecting appropriate input nodes for specific outputs is crucial. In this study, the output is photoneutron yield cross section σxn. Over 27,000 σxn data points from EXFOR [?] for nuclei from ^{6}Li to ^{239}Pu at incident energies above neutron separation energy were collected. The minimum input nodes for studying σxn are target charge number Z, target mass number A, and incident γ-particle energy . This baseline BNN is abbreviated as BNN-ZAE and illustrated in Fig. 1 Figure 1: see original paper.

We demonstrate that BNNs can be improved by incorporating known physics. Photoneutron yield cross sections σxn as functions of incident energy exhibit

Lorentzian shapes with two components. The Lorentzian parameters are peak energy Ei, width Γi, and strength si:

σxn = (cid:88) i=1,2 σTRKsi 2Γi [2 − E2 i]2 + (Γi)2 ,

Fig. 1 shows (a) BNN-ZAE with input nodes Z, A, ; (b) BNN-OPT with optimal input nodes including ground-state properties; and (c) Lorentzian function-based BNN (LBNN) incorporating Lorentzian shape and empirical parameter formulas.

The BNN is a numerical algorithm. In physics, BNNs typically learn residuals from physics-motivated models to fine-tune them, with main physics information contained in the initial prediction. In our previous work [?], we introduced a method providing physics guidance through the input layer without requiring initial physics-motivated model predictions. This method is applied here to select optimal ground-state properties as input neurons for predicting σxn. Details are provided in Ref. [?]. Briefly, various combinations of ground-state properties are tested as input nodes, with the optimal combination selected based on minimal deviation between predictions and data. The optimal input nodes are:

X = {Sn, Qβ, B, A, \$ \$2, },

where Sn is neutron separation energy, Qβ is β^- decay energy, B is binding energy per nucleon, A is mass number, \$ \$2 is quadrupole deformation parameter, and is incident photon energy. This model is abbreviated as BNN-OPT and illustrated in Fig. 1(b). Notably, charge number Z is not used in BNN-OPT. Since only stable nuclei have experimental photoneutron yield cross-section data, and Z and A are strongly correlated for stable nuclei (see Fig. 1 in Ref. [?]), including Z in addition to A does not improve predictions.

The subscripts i = 1 and 2 denote the two components, and σTRK expresses the cross section via the Thomas-Reiche-Kuhn sum rule. The Lorentzian function maps hidden nodes to output cross sections, as shown in Fig. 1(c). Beyond the Lorentzian shape, known physics includes empirical formulas for Lorentzian parameters:

E1 = H1A−1/3 − H2\$ 2, $E2 = H1A - 1/3 + H2\ 2, \Gamma 1 = H3 - H4\ 2, \Gamma 2 = H3 + H4\ 2, s1 = H5 - H6\ 2, s2 = H5 + H6$ \$2,

where Hi (i = 1, …, 6) are empirical parameters. These formulas are incorporated into the BNN, creating a Lorentzian function-based BNN (LBNN). As shown in Fig. 1(c), solid black lines indicate that all input nodes calculate empirical parameters H1 through H6, which together with inputs A and \$ \$2 determine Lorentzian parameters E1, E2, Γ1, Γ2, s1, and s2 via Eq. (11). The Lorentzian parameters depend on A and \$ \$2 through known physical relationships in Eq. (11), while their dependence on other input nodes is unknown and determined numerically during training. Solid and dashed lines distinguish physical from numerical dependencies. Energy is an input node but is not used to calculate the hidden layer because its relationship to the output cross section is known to follow the Lorentzian shape. In BNN-ZAE and BNN-OPT, the energy dependence is a black box; in LBNN, parts of this black box are opened.

III. Results & Discussions

Three BNN variants are evaluated: BNN-ZAE, BNN-OPT, and LBNN. The latter two incorporate physics guidance through improved input nodes and Lorentzian shape considerations. We assess these models by comparing their photoneutron yield cross-section predictions.

Root-mean-square (RMS) deviations between predictions and data are calculated as:

RM S = (cid:118) (cid:117) (cid:117) (cid:116) Nd(cid:88) (cid:16) log σ(n) p − log σ(n) (cid:17)2

where σp is predicted cross section and σd is experimental data. Log-scaling is used because σd values span four orders of magnitude from 10^{-3} to 10 b.

Fig. 2 [Figure 2: see original paper] shows RMS deviations between data and BNN-ZAE predictions as functions of iteration step. Fig. 2(a) compares cases with 1, 2, and 3 hidden layers (10 nodes each). All RMS deviations converge within 1000 iteration steps, with final values of 0.226, 0.219, and 0.214 for 1, 2, and 3 hidden layers, respectively. More hidden layers marginally improve training data reproduction, but the effect is weak. Fig. 2(b) tests hidden node numbers (10, 30, 100) in a single hidden layer. Convergence is slower for more nodes: 1000 steps are needed for 10 and 30 nodes, but 2000 steps for 100 nodes. RMS deviations at 4000 steps are 0.226, 0.229, and 0.235 for 10, 30, and 100 nodes, respectively, with similar performance for 10 and 30 nodes but worse for 100 nodes. Fig. 2(c) compares activation functions (sigmoid, tanh, softplus) for a single hidden layer with 30 nodes. Sigmoid performs best. Subsequent calculations use three hidden layers with 30 nodes each and sigmoid activation.

Fig. 3 [Figure 3: see original paper] compares prediction errors for the three BNN types. Fig. 3(a) shows RMS deviations versus iteration step. All cases converge similarly, with 4000 steps being sufficient. RMS deviations at 4000 steps are 0.198 for BNN-OPT, 0.206 for LBNN, and 0.214 for BNN-ZAE. While varying numerical parameters (hidden layers and nodes) does not improve the network (Fig. 2), incorporating known physics of observables is key. Photoneutron reaction effects such as isospin dependence and shape effects [**?**, **?**, **?**] indicate cross-section dependence on nuclear ground-state properties. BNN-OPT uses ground-state property data in its input layer, while LBNN incorporates Lorentzian shape knowledge. Both aspects reduce RMS deviations compared to BNN-ZAE.

Fig. 3(b) shows distributions of prediction errors log σp − log σd. A value of 1 means the prediction is 10 times larger than data; -1 means 10 times smaller. Cases with |log σp − log σd| > 1 occur in less than 0.1% of samples.

Most samples fall between -0.1 and 0.1, indicating agreement within 1.26 times. Specifically, these comprise 48.0% of BNN-ZAE samples, 57.1% of BNN-OPT samples, and 61.6% of LBNN samples. LBNN shows the largest percentage and most symmetrical error distribution, making it superior to BNN-OPT.

We further evaluate the three BNNs by comparing predictions for spherical nuclei ^{92}Zr, ^{112}Sn, and ^{206}Pb. Fig. 4 [Figure 4: see original paper] shows cross sections versus incident energy. Spherical nuclei typically display one main Lorentzian component in their photoneutron excitation functions, which is observed in the experimental data for these nuclei. LBNN reproduces Lorentzian peak positions and values well, while BNN-ZAE and BNN-OPT underestimate the peak position for ^{92}Zr and peak value for ^{112}Sn.

Abundant data with experimental errors (statistical and systematic) are shown as error bars. Data were resampled inversely proportional to experimental errors for training, emphasizing low-error data. After 4000 iteration steps, 100 samples calculated prediction standard deviations and uncertainties shown as shaded bands. In energy regions with data, BNN-ZAE and BNN-OPT show small uncertainties, but large uncertainties would be expected in extrapolations. The Lorentzian function constrains both predictions and uncertainties in LBNN, giving consistent uncertainties for interpolations and extrapolations in logarithmic coordinates. Uncertainties are small due to abundant data and originate from Monte Carlo techniques. The Lorentzian function is only approximate; it does not account for the threshold at = Sn, making predictions below threshold meaningless.

For axially deformed nuclei, photoneutron yield cross sections show two main Lorentzian shapes, with peak separation positively correlated with deformation parameter $ $2 according to time-dependent Hartree-Fock calculations [**?**]. Data for deformed nuclei ^{31}P, ^{75}As, and ^{165}Ho are shown in Fig. 5 [Figure 5: see original paper] with $ $2 values of -0.22, -0.24, and 0.28, respectively. Two peaks are clear for ^{165}Ho, faint for ^{75}As, and difficult to distinguish for ^{31}P due to abundant but noisy data. However, the broad peak is consistent with two close Lorentzian components.

Predictions with confidence intervals are shown as curves and shaded bands. BNN-ZAE reproduces overall trends for ^{31}P and ^{75}As but slightly overestimates ^{31}P cross sections and misses the two obvious peaks for ^{165}Ho, grossly overestimating at = 14 MeV where data show 0.25 b. BNN-OPT provides smaller RMS deviations than BNN-ZAE but wider confidence intervals. BNN-OPT shows overfitting when extrapolating to low-energy regions (< 10 MeV for ^{31}P and ^{75}As), with confidence intervals predicting increasing cross sections at decreasing energies—contradicting experimental observations.

LBNN reproduces data better than the other models. It considers two Lorentzian shapes related to $ $2 (Fig. 1(c)), correctly predicting two peaks for deformed nuclei. LBNN underestimates ^{31}P cross sections at = 21.5 MeV, where calculations show a valley between Lorentzian peaks but data show a weak peak. This weak peak may reveal substructure beyond the main Lorentzian shapes, also observed in ^{206}Pb near = 25 MeV. Since this substructure lacks physics-motivated explanation, it was not included in the network. The improvement from BNN-OPT to LBNN supports incorporating such substructure after its properties are revealed.

IV. Conclusion

Photoneutron yield cross sections as functions of charge number Z, mass number A, and incident energy were studied using BNN-ZAE. Numerical parameters were varied to test the model, revealing that the sigmoid activation function best realized input-output nonlinearity and produced smallest prediction deviations. However, increasing hidden layers from 1 to 3 or hidden nodes from 10 to 100 did not improve BNN-ZAE predictions.

Following the method of Ref. [**?**], physics guidance was provided through the input layer. Photoneutron reaction effects such as isospin dependence and shape effects [**?**, **?**, **?**] indicate cross-section dependence on ground-state properties. Based on this knowledge, optimal ground-state properties were selected as input neurons, creating the BNN-OPT model. BNN-OPT showed smaller deviations from data than BNN-ZAE.

Further improvement came from incorporating the Lorentzian shape of photoneutron yield cross sections. The Lorentzian function mapped hidden nodes to output cross sections, and empirical Lorentzian parameter formulas linked input nodes to outputs. This Lorentzian function-based BNN (LBNN) was evaluated against BNN-ZAE and BNN-OPT for spherical nuclei (^{92}Zr, ^{112}Sn, ^{206}Pb) and deformed nuclei (^{31}P, ^{75}As, ^{165}Ho). For spherical nuclei with single Lorentzian components, all three models reproduced main trends, but LBNN performed best. For axially deformed nuclei with two Lorentzian shapes, only LBNN reproduced the two peaks, because it explicitly considers two Lorentzian shapes related to quadrupole deformation parameters $ $2.

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Data Availability Statement: The experimental data used in this study are available from the EXFOR database [**?**].

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References

[1] Z. Niu, H. Liang, Nuclear mass predictions based on bayesian shell effects.

Phys. Lett. B 778, 48–53 (2018). Doi: 10.1016/j.physletb.2018.01.002
[2] Z.A. Wang, J. Pei, Y. Liu, et al., Bayesian evaluation of incomplete fission yields. Phys. review letters 123, 122501 (2019). Doi: 10.1103/PhysRevLett.123.122501
[3] R. Wang, Z. Zhang, L.W. Chen, et al., Constraining the in-medium nucleon-nucleon cross section from the width of nuclear giant dipole resonance. Phys. Lett. B 807, 135532 (2020). Doi: 10.1016/j.physletb.2020.135532
[4] X.C. Ming, H.F. Zhang, R.R. Xu, et al., Nuclear mass based on the multi-task learning neural network method. Nucl. Sci. Tech. 33, 48 (2022). Doi: 10.1007/s41365-022-01031-z
[5] Z.P. Gao, Y.J. Wang, H.L. Lü, et al., Machine learning the nuclear mass. Nucl. Sci. Tech. 32, 109 (2021). Doi: 10.1007/s41365-021-00956-1
[6] C.W. Ma, X.B. Wei, X.X. Chen, et al., Precise machine learning models for fragment production in projectile fragmentation reactions using bayesian neural networks. Chin. Phys. C 46, 074104 (2022). Doi: 10.1088/1674-1137/ac5efb
[7] K. Gernoth, J. Clark, J. Prater, et al., Neural network models of nuclear systematics. Phys. Lett. B 300, 1–7 (1993). Doi: 10.1016/0370-2693(93)90738-4
[8] S. Athanassopoulos, E. Mavrommatis, K. Gernoth, et al., Nuclear mass systematics using neural networks. Nucl. Phys. A 743, 222–235 (2004). Doi: 10.1016/j.nuclphysa.2004.08.006
[9] D. Benzaid, S. Bentridi, A. Kerraci, et al., Bethe–weizsäcker semiempirical mass formula coefficients 2019 update based on ame2016. Nucl. Sci. Tech. 31, 9 (2020). Doi: 10.1007/s41365-019-0696-0
[10] N. Costiris, E. Mavrommatis, K.A. Gernoth, et al., Decoding β-decay systematics: A global statistical model for β-half-lives. Phys. Rev. C 80, 044332 (2009). Doi: 10.1103/PhysRevC.80.044332
[11] T. Bayram, S. Akkoyun, S.O. Kara, A study on ground-state energies of nuclei by using neural networks. Annals Nucl. Energy 63, 172–175 (2014). Doi: 10.1016/j.anucene.2013.07.039
[12] Z. Niu, H. Liang, B. Sun, et al., Predictions of nuclear β-decay half-lives with machine learning and their impact on r-process nucleosynthesis. Phys. Rev. C 99, 064307 (2019). Doi: 10.1103/PhysRevC.99.064307
[13] W. Jiang, G. Hagen, T. Papenbrock, Extrapolation of nuclear structure observables with artificial neural networks. Phys. Rev. C 100, 054326 (2019). Doi: 10.1103/PhysRevC.100.054326
[14] X.X. Dong, R. An, J.X. Lu, et al., Novel bayesian neural network based approach for nuclear charge radii. Phys. Rev. C 105, 014308 (2022). Doi: 10.1103/PhysRevC.105.014308
[15] D. Wu, C. Bai, H. Sagawa, et al., Calculation of nuclear charge radii with a trained feed-forward neural network. Phys. Rev. C 102, 054323 (2020). Doi: 10.1103/PhysRevC.102.054323
[16] X. Zhang, X. Liu, Y. Huang, et al., Determining impact parameters of heavy-ion collisions at low-intermediate incident energies using deep learning with convolutional neural networks. Phys. Rev. C 105, 034611 (2022). Doi: 10.1103/PhysRevC.105.034611

[17] X.Z. Li, Q.X. Zhang, H.Y. Tan, et al., Fast nuclide identification based on a sequential bayesian method. Nucl. Sci. Tech. 32, 143 (2021). Doi: 10.1007/s41365-021-00982-z

[18] H.R. Liu, Y.X. Cheng, Z. Zuo, et al., Discrimination of neutrons and gamma rays in plastic scintillator based on pulse-coupled neural network. Nucl. Sci. Tech. 32, 82 (2021). Doi: 10.1007/s41365-021-00915-w

[19] T.Y. Huang, Z.G. Li, K. Wang, et al., Hybrid windowed networks for on-the-fly doppler broadening in rmc code. Nucl. Sci. Tech. 32, 62 (2021). Doi: 10.1007/s41365-021-00901-2

[20] K. Chen, L.B. Zhang, J.S. Liu, et al., Robust restoration of low-dose cerebral perfusion ct images using ncs-unet. Nucl. Sci. Tech. 33, 30 (2022). Doi: 10.1007/s41365-022-01014-0

[21] Y.J. Ma, Y. Ren, P. Feng, et al., Sinogram denoising via attention residual dense convolutional neural network for low-dose computed tomography. Nucl. Sci. Tech. 32, 41 (2021). Doi: 10.1007/s41365-021-00874-2

[22] R. Utama, J. Piekarewicz, H. Prosper, Nuclear mass predictions for the crustal composition of neutron stars: A bayesian neural network approach. Phys. Rev. C 93, 014311 (2016). Doi: 10.1103/PhysRevC.93.014311

[23] R. Utama, W.C. Chen, J. Piekarewicz, Nuclear charge radii: density functional theory meets bayesian neural networks. J. Phys. G: Nucl. Part. Phys. 43, 114002 (2016). Doi: 10.1088/0954-3899/43/11/114002

[24] L. Neufcourt, Y. Cao, W. Nazarewicz, et al., Bayesian approach to model-based extrapolation of nuclear observables. Phys. Rev. C 98, 034318 (2018). Doi: 10.1103/PhysRevC.98.034318

[25] C.W. Ma, D. Peng, H.L. Wei, et al., Isotopic cross-sections in proton induced spallation reactions based on the bayesian neural network method. Chin. Phys. C 44, 014104 (2020). Doi: 10.1088/1674-1137/44/1/014104

[26] J. Bai, Z. Niu, B. Sun, et al., The description of giant dipole resonance key parameters with multitask neural networks. Phys. Lett. B 815, 136147 (2021). Doi: 10.1016/j.physletb.2021.136147

[27] X. Wang, L. Zhu, J. Su, Providing physics guidance in bayesian neural networks from the input layer: The case of giant dipole resonance predictions. Phys. Rev. C 104, 034317 (2021). Doi: 10.1103/PhysRevC.104.034317

[28] G. Baldwin, G. Klaiber, Photo-fission in heavy elements. Phys. Rev. 71, 3 (1947). Doi: 10.1103/PhysRev.71.3

[29] M.T. Jin, S.Y. Xu, G.M. Yang, et al., Yield of long-lived fission product transmutation using proton-, deuteron-, and alpha particle-induced spallation. Nucl. Sci. Tech. 32, 96 (2021). Doi: 10.1007/s41365-021-00933-8

[30] V. Plujko, O. Gorbachenko, R. Capote, et al., Giant dipole resonance parameters of ground-state photoabsorption: Experimental values with uncertainties. At. Data Nucl. Data Tables 123, 1–85 (2018). Doi: 10.1016/j.adt.2018.03.002

[31] T. Kawano, Y. Cho, P. Dimitriou, et al., Iaea photonuclear data library 2019. Nucl. Data Sheets 163, 109–162 (2020). Doi: 10.1016/j.nds.2019.12.002

[32] D. Savran, T. Aumann, A. Zilges, Experimental studies of the pygmy dipole resonance. Prog. Part. Nucl. Phys. 70, 210–245 (2013). Doi: 10.1016/j.ppnp.2013.02.003

[33] A. Bracco, E. Lanza, A. Tamii, Isoscalar and isovector dipole excitations: Nuclear properties from low-lying states and from the isovector giant dipole resonance. Prog. Part. Nucl. Phys. 106, 360–433 (2019). Doi: 10.1016/j.ppnp.2019.02.001

[34] V. Semkova, N. Otuka, M. Mikhailiukova, et al., in EPJ Web of Conferences, Exfor–a global experimental nuclear reaction data repository: Status and new developments. Vol. 146, EDP Sciences, 2017, p. 07003, doi: 10.1051/epjconf/201714607003

[35] J.Y. Tang, Q. An, J.B. Bai, et al., Back-n white neutron source at csns and its applications. Nucl. Sci. Tech. 32, 11 (2021). Doi: 10.1007/s41365-021-00846-6

[36] Y.T. Li, W.P. Lin, B.S. Gao, et al., Development of a low-background neutron detector array. Nucl. Sci. Tech. 33, 41 (2022). Doi: 10.1007/s41365-022-01030-0

[37] D.J. MacKay, A practical bayesian framework for backpropagation networks. Neural computation 4, 448–472 (1992). Doi: 10.1162/neco.1992.4.3.448

[38] X. Wang, L. Zhu, J. Su, Providing physics guidance in bayesian neural networks from the input layer: The case of giant dipole resonance predictions. Phys. Rev. C 104, 034317 (2021). Doi: 10.1103/PhysRevC.104.034317

[39] D. Pandit, S. Bhattacharya, D. Mondal, et al., Role of fluctuations in a thermal phase transition in a nucleus probed via the giant dipole resonance. Phys. Rev. C 99, 024315 (2019). Doi: 10.1103/PhysRevC.99.024315

[40] J. Su, Constraining symmetry energy at subnormal density by isovector giant dipole resonances of spherical nuclei. Chin. Phys. C 43, 064109 (2019). Doi: 10.1088/1674-1137/43/6/064109

[41] A.A.B. Mennana, Y.E. Bassem, M. Oulne, Giant dipole resonance and shape evolution in nd isotopes within tdhf method. Phys. Scripta 95, 065301 (2020). Doi: 10.1088/1402-4896/ab73d8

Note: Figure translations are in progress. See original paper for figures.