Spectrum of Engineering Sciences
ISSN (e) 3007-3138 **(p)** 3007-312X
Volume 3, Issue 12, 2025

SIMULATION OF NEURAL NETWORK IN ALFVEN-SPIN WAVE PROPAGATION THROUGH FERROMAGNETIC SEMICONDUCTOR WITH DEEP LEARNING

Muhammad Najam Shaikh[*1], **Muhammad Adnan**[2], **Naeem Ahmed Ibupoto**[3],
Qadir Bukhsh Yasir[4], **Muhammad Hassan Qureshi**[5], **Ahmed Asghar Memon**[6], **Laiba Najam**[7]

[*1,2,3,4,5,7]*Department of Physics, Government College University, Hyderabad.*
[4]*College of Oceanography, Hohai University of Nanjing 21110, RP China.*
[6]*Depart. of Computer Science & related studies, Hyderabad Institute for Technology & Management Sciences (HITMS)*

[*1]dr.muhammadnajam.shaikh@gcuh.edu.pk

DOI: https://doi.org/10.5281/zenodo.18530752

Keywords

Article History
Received: 02 November, 2025
Accepted:18 December, 2025
Published: 31 December, 2025

Corresponding Author: *
Muhammad Najam Shaikh

Abstract

The expansion of artificial intelligence (AI) and machine learning (ML) has upped the standard for scientific studies and research, including physics. the development of dynamic graphic models of the physical processes being studied using machine learning and neural network algorithms, which convert theoretical concepts and abstract equations into compelling visual depictions of these phenomena. Purpose of this work is to show in what way computational representations can be used for simulation to analyze the effects of changing number densities of electrons and holes on the Alfven-spin wave propagation through ferromagnetic semiconductor with deep learning. Propagation region, non-propagation regions, cutoff regions and stop bands can all be observed and analyzed perfectly with this tool, in a much easier way. This simulation used machine learning (ML) and neural networks to route huge quantities of data and precisely crack multifaceted, theoretically stated calculations that were previously thought to be beyond computing via assimilating mathematical datasets and physical restraints into a Python-based structure.

1. Introduction

Neural networks (NN) and machine learning (ML) are the newest methods for processing and simulating massive amounts of data and accurately solving complicated, theoretically specified equations [1-6]. Neural network feed forward and convolution architectures were employed to anticipate behavior based on input parameters and to approximate solutions [7,8]. Artificial intelligence (AI) and models built on it are becoming practically more and more important in every aspect of life [9-12]. By combining mathematical datasets and physical limits into a Python-based structure, these models made vibrant illustrations of marvels conceivable. The foundation for applying machine learning to physics is still supervised and unsupervised learning. CNN, for example, was used to categorize phase transitions in physical systems [13]. Effective methods that support the modeling of complex systems include random forests, neural networks, and cross validation [14]. ML tools have become strong substitutes for conventional numerical methods; they provide special insights and efficiencies in any field [15].
PIML, or physics-informed machine learning, is a methodology that uses physical rules to inform neural network architecture and training to

improve prediction accuracy in dynamic systems. While PIML incorporates the information of physical restrictions right into the typical design, standard techniques consider data as separate entities. As demonstrated by applications in fluid dynamics, structural mechanics, and plasma physics [14-20], this allows for fairly accurate predictions with little data. For instance, in the multi-physics problem, PIML can simultaneously address linked systems and stochastic processes [21, 22]. Machine learning and neural networks safeguard the versatility, precision, and scalability of the simulations for learning drives.

It is anticipated that developments in AI and quantum computing would enable simulations of hitherto unheard-of complexity, changing physics research and instruction [10,23]. Physics can now simulate complicated systems and ideas that were previously thought to be beyond calculation thanks to neural networks and machine learning. To seek the accurate visualization of the propagation of Alfven-spin waves in ferromagnetic semiconductors, the equation was numerically plotted using machine learning algorithms. The simulation provided accuracy and interpretability by adhering to the basic laws regulating the system through the use of PINNs [24].

Even though machine learning (ML) has shown numerous potential in physics, there are still a lot of unanswered questions. To improve model robustness and application, generative models, adaptive algorithms, and transfer learning are being investigated [25]. Furthermore, the intricacy of physical systems frequently necessitates the usage of high-dimensional information depictions, which may lead to computational inefficiencies and overfitting. It is anticipated that these methods will lead to advances in material science, astrophysics, cosmology, and other fields.

For a composite magnetic-semiconducting medium, the propagation of coupled Alfven-spin waves was examined and a linear dispersion relation has been obtained using a model of an infinite composite media magnetized along the direction of propagation [26-29]. Mathematical studies demonstrate the correlation among the coupled waves' propagation frequency and wave number.

A computational model is used to analyze the effects of changing number density on the propagation of Alfven-spin wave through ferromagnetic semiconductor with deep learning. Propagation region, non-propagation regions and cutoff regions can all be observed and analyzed perfectly by incorporating calculated datasets and physical restrictions into a Python-built background. Neural networks and machine learning (ML) were used in this simulation to handle enormous volumes of data.

Methodology

Dispersion relation of coupled Alfven-spin wave

Propagation of waves in composite media, such as magnetic-semiconducting media, are being studied for variety of theoretical and experimental purposes. The modeling of ferromagnetic-semiconductor devices for spintronic was covered [30]. Alfven-spin wave coupled dispersion relation were obtained by Muhammad Najam Shaikh and Rashid Ali [26]. They additionally investigated the dependency of wave number on the propagation frequency for a usual composite ferromagnetic-semiconductor.

$$\frac{c^2k^2}{\omega^2} = \left[1 + \frac{c^2\mu_o\rho}{B_o^2}\right]\left[1 \pm \frac{\mu_o\gamma M_o}{\omega \pm \mu_o\gamma(H_o + D_{ex}k^2)}\right] \tag{1}$$

Above coupled dispersion relation remains a quadratic equation for k^2 that provides

$$\frac{c^2k^2}{\omega^2}=\frac{1}{2}\left\{\left(1+\frac{c^2\mu_o\rho}{B_o^2}\right)-\left(\frac{c^2}{\omega^2}\frac{\mu_o\gamma H_o\pm\omega}{\mu_o\gamma D_{ex}}\right)\right.$$
$$\left.\pm\left[\left\{\left(1+\frac{c^2\mu_o\rho}{B_o^2}\right)+\left(\frac{c^2}{\omega^2}\frac{\mu_o\gamma H_o\pm\omega}{\mu_o\gamma D_{ex}}\right)\right\}^2+4\frac{c^2}{\omega^2}\frac{\mu_o\gamma M_o}{\mu_o\gamma D_{ex}}\left(1+\frac{c^2\mu_o\rho}{B_o^2}\right)\right]^{1/2}\right\} \quad (2)$$

A computational model is used to analyze the effects of changing number density on the propagation of Alfven-spin wave through ferromagnetic semiconductor with deep learning.

2.1. Dataset Preparation, Architecture, Tools and Libraries

The phase velocity vs propagation frequency—more precisely, a plot of $\omega^2/c^2k^2 = v_\varphi^2/c^2$, is represented using a feed forward neural network. This is modeled by utilizing a combination of PyTorch and visualization tools. For deep learning models, numerical data representation, visualizations, and animations, various libraries are utilized, including torch, numpy, matplotlib, and FuncAnimation. Simulations employing deep learning, machine learning, neural networks like PINNs, and reinforcement approaches are configured using subsequent parameters. The number of times the full training dataset is run through the model during training is represented by epochs in machine learning. Over time, accuracy increases as each epoch modifies the model's parameters to reduce errors. As previously mentioned[mine], we employ the succeeding mathematical values related with a usual composite ferromagnetic-semiconducting medium. Electron and hole number densities (measured in per cubic meter) $n_e = n_h = n_o$ from $10^{18}m^{-3}$ to $10^{22}m^{-3}$, dielectric constant $\varepsilon = 10$, magnetic field (measured in Tesla) $B_o = 0.1$, gyromagnetic ratio (measured in Hz/T) $\gamma = 1.76 \times 10^{11}$, exchange constant ($5 \times 10^{-2}$ in SI units) $D_{ex} = 5 \times 10^{-9}\ Oe/cm^2$ and effective masses of electrons and holes $m_{e,h}^* = 0.01m_{e,h}$ are all almost identical in numerical analysis, despite the fact that electrons typically have lesser effective masses as compared with holes. On the other hand, precession and magnetization frequencies, normalized with plasma frequencies, are provided by $\mu_o\gamma H_o/\omega_{pe} = 0.1$ and $\mu_o\gamma M_o/\omega_{pe} = 0.01$ respectively. Whereas the propagation frequency is taken from 10^9 to 10^{12}Hz.

3. Discussion

3.1. Physics-Informed Neural Networks (PINNs) for the simulation of dispersion relation of coupled Alfven-spin wave

Propagation of Alfven-spin wave through a ferromagnetic-semiconducting medium has variety of applications in device fabrication. However, it is difficult for students and academics to comprehend due to its mathematical complexity. In order to get around this, physics-informed neural networks (PINNs) were programmed to provide an animated visual model that intuitively and less abstractly models the dispersion relation of the coupled Alfven-spin wave. By converting abstract mathematics into a dynamic visual story, this method seeks to improve conceptual understanding in addition to computational correctness. Neural networks, especially Physics Informed Neural Networks (PINNs), provide an excellent substitute for this approach due to its potential computing demands [4—6]. In order to enable the network to approximate solutions with exceptional efficiency and scalability, the governing equations are directly embedded into the loss function.

Herein study, we employed a neural network to plot phase velocity against propagation frequency—more specifically, a plot of $\omega^2/c^2k^2 = v_\varphi^2/c^2$ versus ω. Where $v_\varphi = \omega/k$ is the coupled wave's phase velocity. This network is designed to minimize a physics-informed loss while ensuring adherence to the equations' limitations, allowing students to link theoretical equations with observable occurrences.

Neural network is used to simulate the dispersion relation of coupled Alfven-spin wave for the lower and upper signs of polarization in equation (2), for different number densities such as $10^{18}, 10^{20}, 10^{21}$, and 10^{22}. Following figures represent four cases of each of these models (total 8 cases). These three-dimensional models are used to represent dispersion relation of coupled Alfven-spin wave. They are discussed one by one.

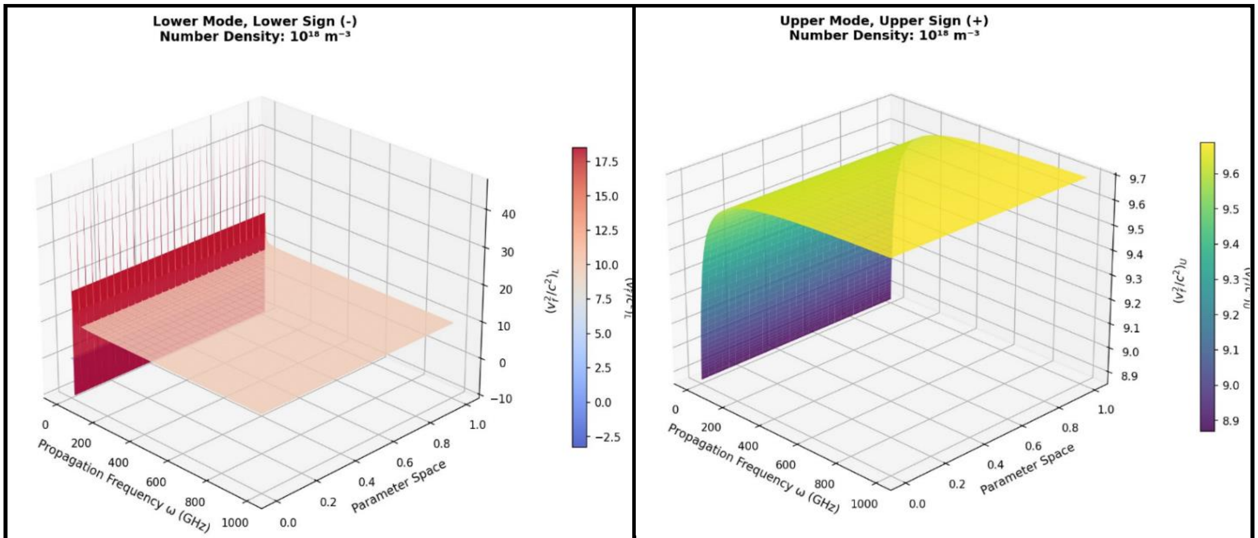

Fig.1a

Fig.1b

Fig.1a & Fig.1b, illustrates how the propagation frequency ω affects the v_φ^2/c^2 with lower and upper signs of polarization respectively at a number density of 10^{18}. Fig.1a shows regions of both non-propagation and propagation, whereas; Fig.1b shows a continuous region of propagation.

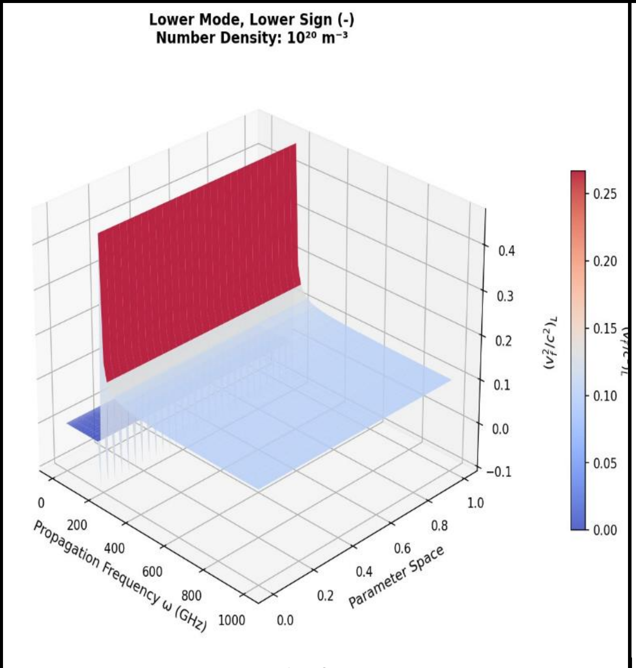

Fig.2a

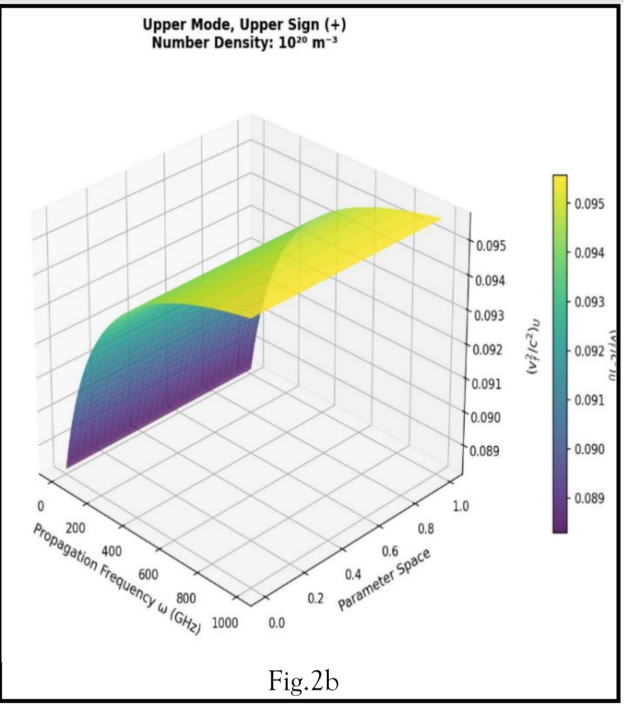

Fig.2b

Fig.2a & Fig.2b, illustrates how the propagation frequency $\boldsymbol{\omega}$ affects the $\boldsymbol{v_\varphi^2/c^2}$ with lower and upper signs of polarization respectively at a number density of $\mathbf{10^{20}}$. Fig.2a shows regions of both non-propagation and propagation along with a cutoff region and a stop band, whereas; Fig.2b shows a continuous region of propagation.

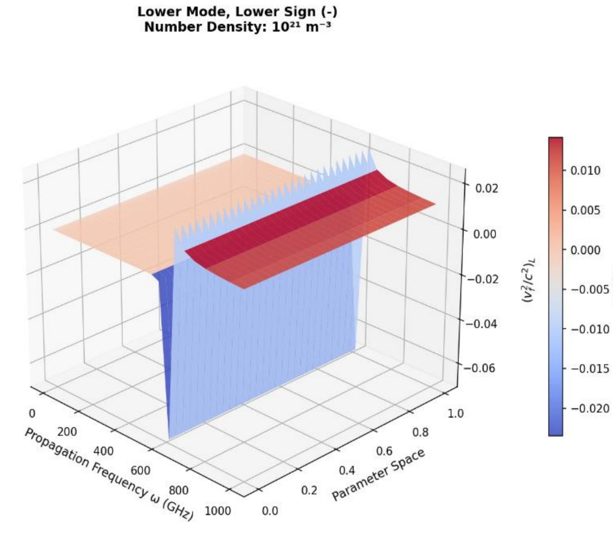

Fig.3a

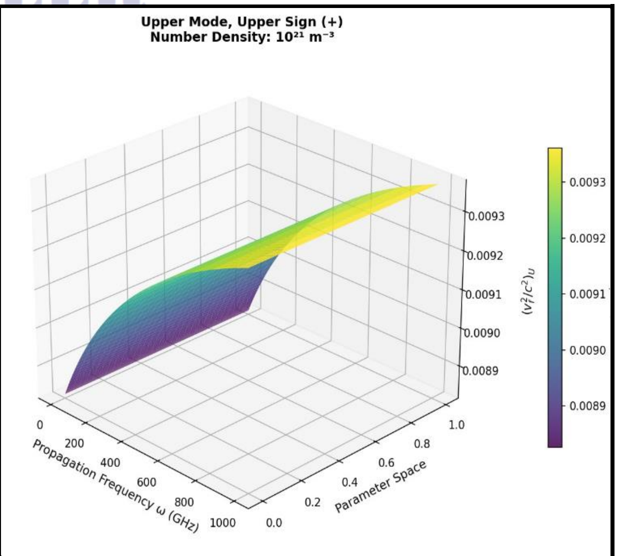

Fig.3b

Fig.3a & Fig.3b, demonstrates how the propagation frequency $\boldsymbol{\omega}$ affects the $\boldsymbol{v_\varphi^2/c^2}$ with lower and upper signs of polarization respectively at a number density of $\mathbf{10^{21}}$. Fig.3a shows regions of both non-propagation and propagation along with a cutoff region and a stop band, whereas; Fig.3b shows a continuous region of propagation.

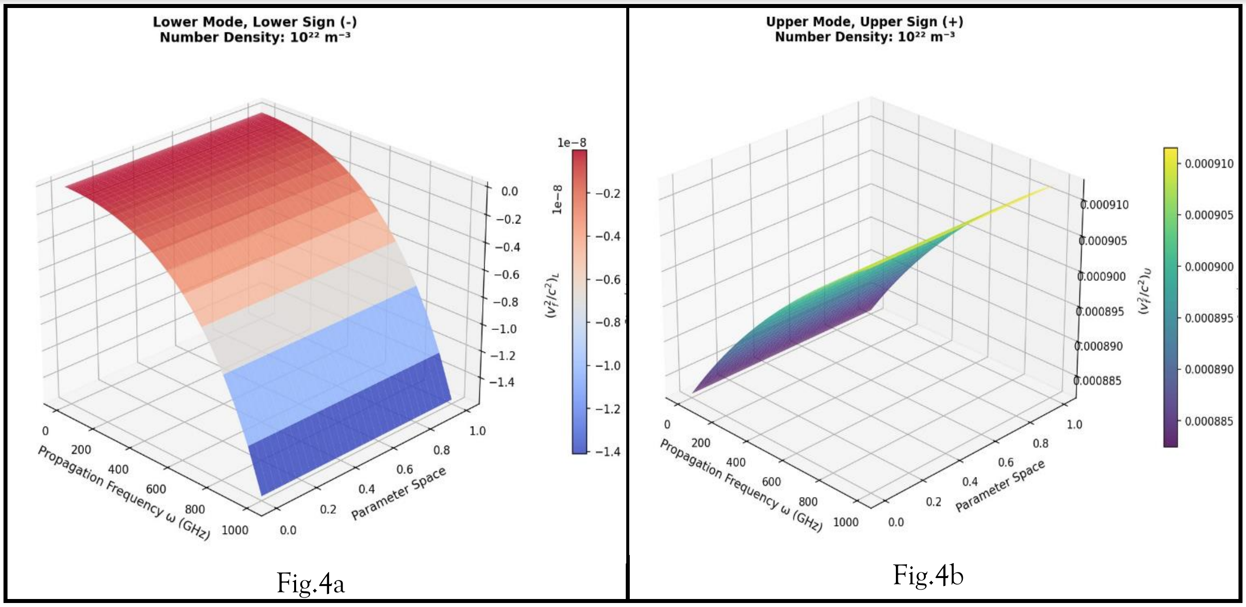

Fig.4a

Fig.4b

Fig.4a & Fig.4b, illustrates how the propagation frequency ω affects the v_{φ}^2/c^2 with lower and upper signs of polarization respectively at a number density of 10^{22}. Fig.4a and Fig.4b both show continuous regions of propagation.

4. Results

This model illustrates the features of coupled Alfven-spin wave which propagates through a ferromagnetic-semiconductor by exercise a physics-informed neural network (PINN), assumed the different values of number densities of electrons and holes. An approximation of the phase velocity for various propagation frequency values was successfully found by the model.

During training, it was noted that periodic snapshots of the phase velocity were tuned toward the real solution. The phase velocity estimate changed dynamically during epochs, as demonstrated by the animated graphic. Phase velocity evolved from an initial random state to a highly accurate representation with the variation in the propagation frequency, demonstrating the ability of PINNs to capture propagation characteristics.

The findings demonstrated that coupled Alfven-spin waves propagating through ferromagnetic semiconductors may be effectively analyzed by combining machine learning approaches with conventional physics models. In addition to increasing computational efficiency, the hybrid approach enables a more thorough examination of system characteristics. The findings also support the application of physics-informed neural networks as a flexible method for resolving physical problems.

The dispersion relation of a coupled Alfven-spin wave for the bottom and upper signs of polarization, for various number densities like $10^{18}, 10^{20}, 10^{21}$, and 10^{22}, is simulated using a neural network. The dispersion relation of a linked Alfven spin wave is represented by these three-dimensional models. These modes give regions of both non-propagation and propagation along with cutoff region and stop bands.

5. Conclusion

This study used machine learning and PINNs to analyze the propagation of a coupled Alfven-spin wave in a ferromagnetic-semiconductor. Physical laws were incorporated into the training process, rather than relying on standard numerical approximations.

This study uses deep learning to analyze the impact of changing number density on the propagation of Alfven-spin waves via ferromagnetic semiconductors. A Python-based framework is used to incorporate mathematical datasets and physical constraints. This simulation used ML and neural networks to interpret large amounts of data. Equation (2) provides the upper and lower signs of the square root, allowing for numerical analysis of the relationship between v_{φ}^2/c^2 and the propagation frequency ω.

These equations have eight propagation modes for upper and lower polarization signs, respectively. Upper modes exhibit continuous regions of propagation. Lower modes exhibit non-propagation and propagation regions, as well as cutoff and stop bands. The study suggests that machine learning can enhance our understanding of physical events and serve as a foundation for advanced scientific and engineering applications.

6. Future Work

This study concentrated on effect of changing number densities of electrons and holes on the propagation of Alfven-spin wave through ferromagnetic-semiconductor. We are currently working on extending this work to apply the physics-informed neural networks for the propagation characteristics of Alfven-spin waves through ferromagnetic-semiconducting media. Using machine learning (ML) and physics-informed neural networks (PINNs) to solve equations improves their practicality, reliability, and versatility for real-world applications. We will apply multimodal approaches combining experimental data with physics-informed models.

References

Muhammad Najam Shaikh et al., “Simulation of Neural Network in Nano Science with Deep Learning”, *Policy Research Journal*, vol. 3 no. 2, pp. 568-582, 2025. [Online] Available: https://doi.org/10.5281/zenodo.14934716

Muhammad Najam Shaikh et al., “Neural Network in Schrodinger Equation with Deep Learning”, *Dialogue Social Science Review (DSSR)*, vol. 3 no. 1, pp. 1107-1119. [Online] Available: https://www.dialoguesreview.com/index.php/2/article/view/245

Hong Wang, Hengyu Cao, Liang Yang "Machine Learning-Driven Multidomain Nanomaterial Design: From Bibliometric Analysis to Applications", November 21, 2024, [online] Available: https://doi.org/10.1021/acsanm.4c04940

David A. Winkler, "Role of Artificial Intelligence and Machine Learning in Nanosafety", vol. 16, Issue 36, 15 June 2020, [online] Available: https://doi.org/10.1002/smll.202001883

J. Carrasquilla and R. G. Melko, "Machine learning phases of matter", *Nature Physics*, vol. 13, no. 5, pp. 431- 434, 2017. [Online]. Available: https://doi.org/10.1038/nphys4035

Qadir Bakhsh Yasir et al., “Optimising laser shock peening parameters to minimise surface tensile stress on aluminium alloys via ANN-enhanced finite element simulation”,

Journal of Materials Research and Technology, vol. 39, pp. 4298-4306, 2025. [Online]. Available: https://doi.org/10.1016/j.jmrt.2025.10.059

M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving partial differential equations,"*arXiv preprint*, arXiv:1605.01735v1, 2016. [Online]. Available: https://doi.org/10.1016/j.jcp.2018.10.045

H. Behrooz, YM Hayeri “Machine learning applications in surface transportation systems: A literature review” *Appl. Sci.* 2022, *12*(18), 9156; mdpi.com, https://doi.org/10.3390/app12189156

X. E. Song, T. Xue, "General Study about Applications of Artificial Intelligence in Physics", *IJISSET*. 2019, 5(3), pp 43-48, The Benjamin School, Palm Beach Gardens, Florida, USA. [Online]. Available: https://ijisset.org/storage/Volume5/Issue3/IJISSET-050306.pdf

Brohi IA, Najma IA, NU Sohu, BA Laghari, and MN. Shaikh, "*Applications of Artificial Intelligence and Image Processing Using Unmanned Air Vehicles (UAV) for Crop Health Identification*". Sindh Uni. Res. J.- (SS), 2023 55(02), pp 56-62, University of Sindh, Jamshoro, Pakistan. [Online]. Available: https://doi.org/10.26692/surj-ss.v55i02.6532

C. Yan and Y. Zhang, "Local turbulence generation using conditional generative adversarial networks toward Reynolds-averaged Navier–Stokes modeling," *Physics of Fluids*, vol. 35, no. 10, p. 105102, Oct. 2023. [Online]. Available: https://doi.org/10.1063/5.0166031

Radheyshree Agrawal, Paras Tilak, Aryan Devand, Archana Bhatnagar, Piyush Gupta, "Artificial Intelligence in Nanotechnology", pp 239-248, https://doi.org/10.1007/978-981-99-9179-2_18

Alexey Melnikov, Mohammad Kordzanganeh, Alexander Alodjants & Ray-Kuang Lee, "Quantum machine learning: From physics to software engineering," vol. 8, 2023. [Online]. Available: https://doi.org/10.1080/23746149.2023.2165452

Zhongkai Hao, Songming Liu, Yichi Zhang, Chengyang Ying, Yao Feng, Hang Su, Jun Zhu, "Physics-informed machine learning: A survey on problems, methods, and applications, "*International Journal of Computational Physics*", vol. 2, 2023. [Online]. Available: https://doi.org/10.48550/arXiv.2211.08064

Shahid M. Eabd Alrida, Ola D. Obed, Elaf M. Taha, Thamer A. Abdullah, Mustafa M. Hathal, Viola Somogyi, "Applications of artificial intelligence in nanotechnology," Volume 42, Issue 9, pp 1193-1209, 2024. [Online]. Available:https://www.iasj.net/iasj/article/325971

Yunchi Zhou Ying Wang et al., "Application of Machine Learning in Nanotoxicology: A Critical Review and Perspective" pp 14973–14993, August 7, 2024. [Online] Available: https://pubs.acs.org/doi/10.1021/acs.est.4c03328

Mawuli Agboklu, Frederick A Adrah, Prince, Mawuli Agbenyo, Hope Nyavor, "From bits to atoms: Machine learning and nanotechnology for cancer therapy", pp 16-26, March 2024. [Online]. Available: http://dx.doi.org/10.26502/jnr.2688-85210042

Engr. Ahmed Asghar Memon et al., "Optimization of Radio Network Cooperation Using Moran and MOCN", *African Journal of Biomedical Research*, vol. 27, No. 45, pp. 10115-10124, 2024. [Online] Available: https://doi.org/10.53555/AJBR.v27i4S.5619

Shanza Kausar, Nidaa Yousif Amrullah, Muhammad Najam Shaikh, "Revolutionizing Optoelectronics through Photonic Crystals and Metamaterials for Tailored Light-Matter Interactions", *Annual Methodological Archive Research Review*, vol. 3, No. 7, pp. 523-545, 2025.

Qadir Bukhsh Yasir et al., "The Effect of Post Growth Annealing on The Physical Properties of Fe-Doped ZnO Nanostructures", *The International Journal of Modern Sciences and Multidisciplinary Studies(IJMSMS)*, vol. 3, No. 1, pp. 28-41, 2024. [Online] Available: https://journal.gcuh.edu.pk/index.php/ijmsms/article/view/21

Juan Diego Toscanoa et al., "From PINNs to PIKANs: Recent advances in physics-informed machine learning," Volume .1 ,2024. [Online].Available:https://www.researchgate.net/publication/385010051_From_PINNs_to_PIKANs_Recent_Advances_in_Physics-Informed_Machine_Learning

Zhongkai Hao, Songming Liu, Yichi Zhang, Chengyang Ying, Yao Feng, Hang Su, Jun Zhu, "Physics-informed machine learning: A survey on problems, methods, and applications," vol. 2, 2023. [Online]. Available: https://doi.org/10.48550/arXiv.2211.08064

Kanika Dulta, Amanpreet Kaur Virk, Parveen Chauhan, Paras Bohara, Pankaj Kumar Chauhan "Nanotechnology and applications", pp 129-141, Solan, India publisher, Feb.2022. [Online]. Available: https://doi.org/10.1016/B978-0-12-823978-0.00002-2

Juan Diego Toscano, Vivek Oommen, Alan John Varghese, Zongren Zou, Nazanin Ahmadi Daryakenari, Chenxi Wu, George Em Karniadakis, "From PINNs to PIKANs: Recent advances in physics-informed machine learning," vol. 2, 2024. [Online]. Available: https://arxiv.org/abs/2410.13228

Francisco A. Rodrigues, "Machine learning in physics: A short guide," vol. 1, 2023. [Online]. Available: https://doi.org/10.48550/arXiv.2310.10368

Muhammad Najam Shaikh et al., "Coupled Alfven-spin waves in a composite magnetic-semiconducting medium", *Chinese J. Phys.*, vol. 47, No. 3, pp. 336-343, 2009.

Muhammad Najam Shaikh et al., "Coupled waves in the periodic composite magnetic–semiconducting media", *PIER. M.*, vol. 18, pp. 73-84, 2011.

Muhammad Najam Shaikh et al., "Coupled nonlinear waves in a composite magnetic–semiconducting medium", *Phys. Lett. A.*, vol. 374, Issue 29, pp. 2942-2948, 2010.

Muhammad Najam Shaikh et al., "TE surface waves in a plasma sandwich structure", *APhysPolA.*, vol. 127, No. 6, pp. 1625-1629, 2015.

N. Lebedeva and P. Kuivalainen, "Modeling of ferromagnetic semiconductor devices for spintronics", *J. Appl. Phys.*, vol. 93, pp. 9845-9864, 2003. [Online]. Available: https://doi.org/10.1063/1.1575498