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Advances in Artificial Intelligence and Computational Methods: Enhancing Modeling, Prediction, and Optimization

Ambika Tundwal[1], Manjeet Kaur[2], Daljeet Kaur[3]
[1,2,3]*Department of Applied Sciences, Guru Tegh Bahadur Institute of Technology, New Delhi, India*

Abstract: This area of artificial intelligence and computational methods has witnessed tremendous development, especially with the solution of highly complex problems across scientific disciplines. This review brings together the latest advancements in the integration of AI with traditional computational techniques, focusing on their applications in numerical simulations, system optimization, and predictive modeling. Key contributions include AI-augmented finite difference methods for solving partial differential equations, advancements in material and energy systems optimization, and innovative approaches to high-performance computing. Future directions emphasize scalability, interdisciplinary applications, and the integration of emerging technologies such as quantum computing and reconfigurable hardware.

Keywords: Artificial intelligence; Computational methods; complex problems; interdisciplinary applications; emerging technology

I. INTRODUCTION

In recent years, artificial intelligence (AI) has emerged as a transformative force in computational science [1]. AI enables systems to learn from data, thus augmenting traditional computational methods, offering unprecedented capabilities for modeling, prediction, and optimization [2-3]. These advances are particularly critical in addressing complex scientific and engineering challenges, where conventional approaches often fail with scalability, accuracy, or computational efficiency.

The landscape of scientific investigation and industry applications is becoming completely transformed through the integration of AI with computational methods [4]. Traditional computational methods like FDM and FEA have been in use for solving PDEs and simulating physical phenomena since a long time [5-9]. However, these methods consume lots of computation resources and are bound to predefined models with assumptions. AI, with its strong mainstreaming of machine learning (ML) and deep learning (DL), can drive solutions that are adaptive, data-driven, and more capable of handling the complexity of high-dimensional systems [10-12].

This integration is not only enhancing the efficiency of existing methods but also enabling new capabilities, such as real-time predictions and automated decision-making. For instance, AI-driven optimization algorithms are being used to design materials with desired properties, optimize energy systems, and improve hardware performance. Furthermore, the application of AI in high-performance computing (HPC) has introduced innovations in reconfigurable hardware, parallel processing, and quantum computing [13-15].

It cannot be overemphasized how the growing importance of interdisciplinary approaches is emerging. As AI permeates every sphere, ranging from materials science and physics to engineering, it's driving collaboration, bringing computational science, mathematics, and domain-specific disciplines into each other's arms [16-17]. This review intends to provide an overview of all these advancements and to focus on the key applications, emerging trends, and the challenges that lie ahead.

Based on recent studies, the review synthesizes contributions toward a transformative AI-enhanced computational methodology. It addresses a broad scope of topics: from numerical simulations and system optimization to predictive modeling and hardware innovation. Ultimately, it is a call for further research and development in this field, which has been changing dramatically and promises future scientific and technological breakthroughs.

II. AI-ENHANCED NUMERICAL METHODS

A. AI-Augmented Finite Difference Methods for PDEs

Finite difference methods (FDM) are well known to be a foundation for solving partial differential equations, such as modeling phenomena in physics, engineering, and data science, for example [18-21].

They rely on a discretization of both spatial and time domains for a numerical approximation of solutions. The traditional approaches of FDM have limitations: they are often constrained with limitations of grid resolution, stability requirements, and computational load, even in moderately high dimensional or nonlinear problems [22].

AI, in particular through ML and DL, has significantly enriched FDM capability [23]. AI models can adaptively modify computational grids, optimize the time-stepping schemes, and dynamically choose models to suit requirements of specific problems [24]. For example, ML-based algorithms can get high-error regions in real time to concentrate resources on computation in these regions to contribute to maximizing both precision and efficiency [25]. This comes in handy particularly in solving PDEs, which include the heat equation, wave equation, and Laplace's equation [26-28].

In Fig. 1, Contour plot shows the isopotential lines of the 2D Laplace equation solution. The contour levels represent the constant potential values across the computational domain, illustrating the smooth transition of potential in the model. This highlights the role of finite difference methods in solving partial differential equations (PDEs) for real-world applications in physics and engineering.

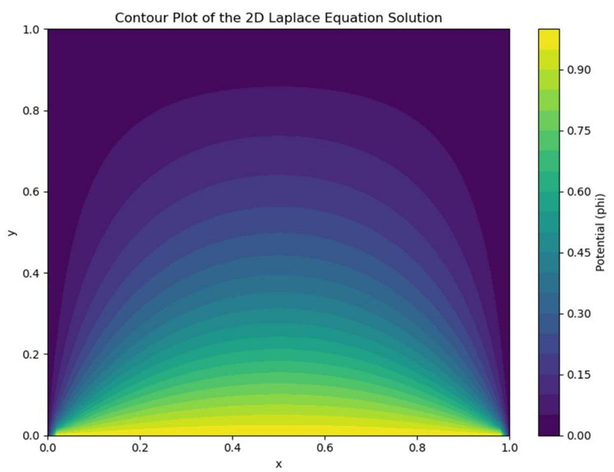

Fig. 1. Contour plot of the 2D Laplace Equation Solution

Fig. 2, depict the 3D surface plot of the potential solution to the 2D Laplace equation. The surface represents the variation of the potential across the grid, providing a clear visualization of the solution's spatial behavior. This plot emphasizes the effectiveness of computational methods in modeling complex physical systems and their potential for AI-enhanced predictions and optimization.

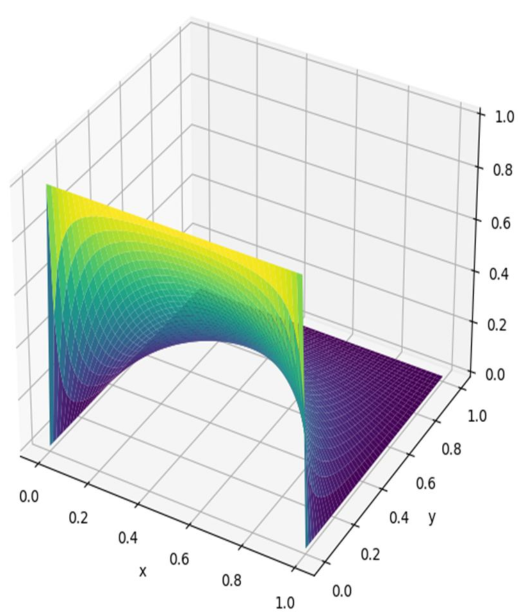

Fig. 2. 3D Surface Plot of the 2D Laplace’s Equation Solution

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In Fig. 3, Heatmap displays the potential solution across the 2D Laplace equation grid. The colors represent the magnitude of the potential, with annotations highlighting areas of interest. This plot demonstrates how visual analytics can be applied to computational models, guiding researchers to focus on key regions, much like how AI models identify significant patterns in data.

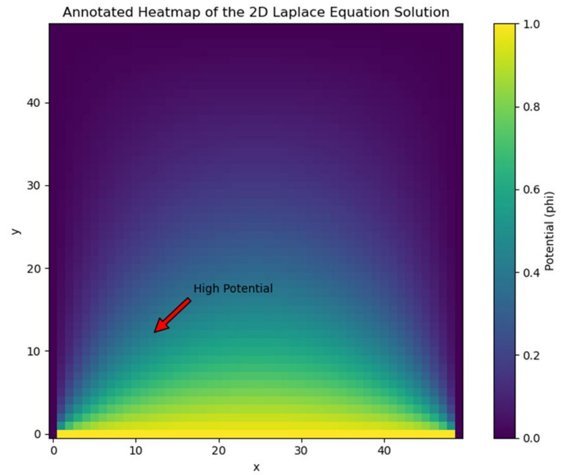

Fig. 3. Heatmap of the 2D Laplace's Equation Solution

Combined color-filled contour plot with overlaid streamlines for the 2D Laplace's equation solution is given in Fig 4. The filled contours show the magnitude of the potential, while the streamlines highlight the gradient direction. This integrated approach exemplifies how computational methods can simultaneously display multiple aspects of a solution, akin to the multi-faceted optimization processes in AI models.

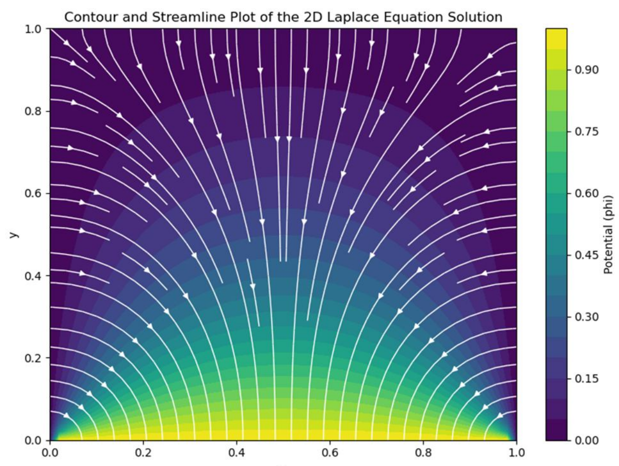

Fig. 4. Contour and Streamline Plot of the 2D Laplace's equation Solution

Okwuwe and Oduselu-Hassan's work exemplifies such improvements [29]. Their work presents AI-injection into FDM to achieve improved accuracy and reduce computational overhead. Using Python-based implementations, it illustrated that AI-enhanced FDM was robust in handling different PDE scenarios-fluid dynamics, climate modeling, wave propagation, and similar others-and could potentially form the basis of new numerical methods where traditional formulations are greatly limited.

B. Applications and Implications

This is a fusion of AI with numerical methods such as FDM and has broad implications across multiple domains [30]. In fluid dynamics, AI-enhanced FDM permits the precise modeling of turbulent flows by dynamically refining grids in regions of high complexity [31-32]. The same methods in climate modeling will improve the accuracy of weather predictions by efficiently handling intricate interactions between atmospheric variables [33-35]. In wave propagation studies, AI-augmented techniques provide high-resolution solutions that are computationally feasible, even for large-scale problems [36].

In addition to these classic scenarios, AI improved numerical techniques find new areas for interdisciplinary studies. For instance, in biomedical engineering, PDEs model certain biological phenomena involving tumor growth or drug diffusion into tissues [37-38]. AI can offer real-time computing, and based on that, aid with decision-making as part of personalized treatment [39]. In geophysics, a similar role they play in making seismic activities available for modeling in precise earthquake predictions, as well as resource exploration scenarios [40].

Future research in this area may expand such AI-augmented approaches to more complex PDEs, such as those that involve multiphysics interactions or stochastic components. In addition, there is a strong need to generalize such techniques for real-world, resource-constrained environments where computational efficiency and scalability are of the essence. Further prospects, based on the synergy of AI approaches with traditional numerical solvers for hybrid frameworks in which the most beneficial aspects from both approaches might be used toward solving the very toughest scientific challenges.

III. ADVANCED COMPUTATIONAL TECHNIQUES

A. Classification and Prediction

Advanced computational techniques have become a necessity in modeling, analyzing, and predicting the behavior of complex systems [41]. ML algorithms, such as neural networks, support vector machines, and decision trees, play a key role in making these capabilities possible [42-43]. ML methods identify patterns, build predictive models, and optimize processes using large datasets, complementing traditional numerical simulations [44].

The review by Krzywanski et al. integrates AI with optimization techniques for material and energy systems [41]. Their results showed that there was a great accuracy and efficiency improvement, and they are of significant value to researchers and practitioners. Key applications of classification and prediction techniques include computational fluid dynamics (CFD), finite element analysis (FEA), and big data analytics [45-46]. For example, in CFD, ML models can predict flow behaviors in turbulent systems, which reduces the need for exhaustive simulations [47-48].

B. Integration of AI in Optimization

Optimization is the backbone of computational science, enhancing engineering, manufacturing, and resource management. Traditional optimization algorithms, for instance the gradient-based approach, appear to be limited in their application in many dimensions when dealing with high dimensional or even non-convex problems [49]. However, AI-centered techniques, especially those that embrace evolutionary approaches, have proven very effective [50].

Evolutionary algorithms, including genetic algorithms (GA), particle swarm optimization (PSO), and differential evolution (DE), are inspired by natural selection to search complex spaces [51-53]. The integration of AI into these methods has led to the development of hybrid techniques that enhance their performance. For example, hyper-heuristic approaches use ML models to adaptively select optimization strategies based on the problem characteristics, ensuring more efficient convergence [54-55].

More recent works are optimization methods based on the vision transformer. They bring fresh perspectives in navigating the meta-loss landscape [56]. It incorporates neural networks and reinforcement learning frameworks that enable the dynamic exploration of parameter spaces. Its applications cover wide domains ranging from engineering design to material synthesis, including optimization of energy systems.

C. Applications Across Domains

These developments have led to the breakthroughs of several domains by advancements in classification, prediction, and optimization. In materials science, AI-based methods predict the properties of material, optimize the manufacturing process, and design novel materials with specified characteristics [57-58]. In energy systems, ML models optimize grid operations, predict energy demands, and enhance the integration of renewable sources [59].

Furthermore, the application of AI in computational methods has revolutionized healthcare, allowing for predictive analytics in patient outcomes, drug discovery, and personalized treatment plans [60 -61]. In finance, these techniques power risk assessment models, fraud detection systems, and algorithmic trading strategies [62-64]. The versatility of AI-driven computational methods highlights their potential to address challenges in interdisciplinary research and real-world applications.

D. Future Directions in Advanced Computational Techniques

The further development of this field requires work on developing more interpretable AI models with guarantees for transparency and trust in critical applications.

There is also the interesting opportunity of using quantum computing to overcome the bottlenecks of computationally intensive tasks such as optimization and prediction in the presence of AI-driven methods. Interdisciplinary collaborations will unlock the full potential of advanced computational techniques, leading to innovations in science and industry.

IV. INNOVATIONS IN MATHEMATICAL MODELING AND HIGH-PERFORMANCE COMPUTING

A. AI-Driven Methods for Simulations and System Optimization

Artificial Intelligence has brought paradigm shifts in the simulation and system optimization, offering more efficient and accurate computational models. The latest development is based on generative models, that is, the GPT-based frameworks, and their application to high-quality simulation [65]. For example, the generation of natural product-like compounds using a GPT-based chemical language model, which has facilitated the streamlining of processes in material and chemical science [66]. These generative models, therefore reduce greatly the computation and time resources requirements to design such a complex system of analysis.

Another area is in AI-driven history data analysis: machine learning-based techniques have applied to enhance character and printed-text recognition and the processing of data [67, 68]. They are not just cultural heritage; they also increase methodologies for more data-driven historical work. Another use of AI involves the advancement in music recommendation applications, which would use APIs for example, those from Spotify. It allows these systems to apply personalized experiences given user preferences [69, 70].

B. Hardware Optimization and Reconfigurable Systems

High-performance computing is witnessing a paradigm shift with the advent of reconfigurable hardware systems [71]. Reconfigurable virtual accelerators [ReVA] and vector register sharing systems have been introduced to efficiently play the computational game [72]. Simulation environments like the Vivado Simulator have been integrated into ReVA systems to improve resource allocation as well as performance [73]. These systems are extremely beneficial for domains where real-time computations have to be performed, such as with machine learning and physics simulations.

Vector register sharing is another innovative approach through which hardware performance is optimized with the capability to share resources among accelerators [74]. The technology reduces latency and energy consumption and is suitable for application in engineering design and optimization of complex tasks. These advances show the critical role hardware innovation plays in supporting AI-driven computations at scale.

C. Applications and Future Prospects

Integration with mathematical modelling and HPC catalyzed significant progress in areas such as drug discovery, engineering design, and high-speed numerical methods. For instance, evolutionary algorithms optimized with AI could be used in solving demanding engineering problems, such as designing aircraft and material synthesis. In much the same manner, high-speed numerical methods for large-scale systems, amongst them condition number computations for linear systems, have made it much easier to carry out computational work in physics and engineering.

Looking forward, the combination of AI, HPC, and mathematical modeling is promising for addressing the complex scientific challenges that are emerging. Future research should focus on the development of scalable AI-driven simulation frameworks and adaptive hardware systems to meet the growing demands of data-intensive applications. Interdisciplinary collaborations will be important to unlock new opportunities and ensure that innovations in these fields continue to drive progress across science and technology.

V. EMERGING TRENDS AND FUTURE DIRECTIONS

A. Quantum Computing and Neuromorphic Devices

Quantum computing and neuromorphic devices are poised to redefine the computational landscape. Quantum computing exploits the principles of quantum mechanics, such as superposition and entanglement, to perform calculations at speeds unattainable by classical computers [76-77]. These technologies have the potential to revolutionize fields like cryptography, optimization, and drug discovery by solving problems that are currently computationally intractable [78]. Emerging quantum algorithms are already demonstrating breakthroughs in simulating molecular structures and optimizing complex supply chains.

Neuromorphic devices, inspired by the architecture of the human brain, mimic neural processes to achieve energy-efficient computations [79].

Their devices are especially designed for pattern recognition, adaptive learning, and real-time decision-making [80]. The neuromorphic hardware with AI allows researchers to create systems that can process huge datasets with minimal levels of energy consumption-a critical requirement for edge computing and autonomous systems.

B. Interdisciplinary Collaborations

The intersection of AI with statistical physics, materials science, and biology is fueling a new generation of interdisciplinary research. The joint efforts are toward solving challenges that require expertise in multiple domains, such as understanding climate dynamics, designing advanced materials, and developing personalized medicine.

For example, for materials science research, AI applications can predict and optimize novel chemical compounds, such that their invention leads to innovations in sustainable production technologies. As a second important application of biology, AI-based model-driven predictions could significantly improve an understanding of data on genomics and allow greater precision in medicine as well as engineering. Statistical physics and AI methods provide new analytical approaches for understanding several complex systems ranging from fluid flow and phase changes, important concepts for both civil and environmental applications.

Creation of frameworks that integrate AI with traditional scientific methodologies, such that they emphasize assimilation, transparent model discovery, and further improvements in prediction accuracy in the real world. Global collaborations among researchers, institutions, and industries will play a critical role in furthering interdisciplinary applications of AI.

C. Emerging Applications and Ethical Considerations

As AI technologies evolve, their applications now range into unprecedented domains, like making ethical decisions on behalf of humans, robot autonomy, and augmented reality. Such progress does come with some associated ethical issues, including issues of bias, privacy, and accountability. Interplay between researchers and policymakers is imperative in establishing and framing responsible use of AI in society through law and ethics.

Emerging applications in AI include climate modeling, autonomous transportation, and human-augmented decision-making, which hold tremendous potential for the solution of global challenges. For instance, AI-driven climate models will provide actionable insights for mitigating the impacts of climate change, while autonomous vehicles promise safer and more efficient transportation systems. Addressing the ethical and technical challenges that arise, the scientific community can unlock AI's full potential for societal benefit.

VI. CONCLUSION

The integration of AI with computational methods represents a fundamental shift in the scientific and engineering research landscape. This review outlines how AI-based advances in numerical methods, optimization techniques, and high-performance computing are meeting current challenges related to scalability, efficiency, and direct applicability in real-world situations. It also shows that integrating traditional computational methods with advanced AI technologies has unlocked previously unattainable opportunities for tackling complex problems in various fields of study.

The future of computational science will be in adapting to emerging technologies, such as quantum computing and neuromorphic devices, that promise to revolutionize areas such as optimization, cryptography, and large-scale simulations. These technologies, combined with AI, will enable researchers to tackle computationally intractable problems, pushing the boundaries of what is scientifically achievable.

Interdisciplinary collaborations continue to be a foundation for progress, fostering innovation and uniting competencies from around different fields. Whether in materials science, healthcare, or climate modeling, the synergy between AI and domain-specific knowledge will drive pioneering discoveries and sustainable solutions to global challenges. Furthermore, ethical considerations should accompany such technological advancements in responsible deployment and equitable benefits toward society.

In conclusion, it is evident that combining AI, traditional computational techniques, and emerging technologies provides a robust framework in addressing certain of the most pressing scientific and engineering problems of our time. As researchers seek out more space to innovate and collaborate, their capacities with AI-enhanced computational methods to reshape industries and serve the world are limitless. This versatile field has all the answers for that future as it enlists science and technology together to forge a new and better world.

REFERENCES

[1] M. Khaleel, A. Jebrel, and D. M. Shwehdy, "Artificial Intelligence in Computer Science," Int. J. Electr. Eng. And Sustain., vol. 2, no. 2, pp. 01–21, 2024. [Online]. Available: https://doi.org/10.5281/zenodo.10937515.

[2] J. Krzywanski, M. Sosnowski, K. Grabowska, A. Zylka, L. Lasek, and A. Kijo-Kleczkowska, "Advanced Computational Methods for Modeling, Prediction and Optimization—A Review," Materials, vol. 17, no. 14, p. 3521, 2024. [Online]. Available: https://doi.org/10.3390/ma17143521.

[3] F. Ekundayo, "Leveraging AI-Driven Decision Intelligence for Complex Systems Engineering," Int J. Res Publ Rev, vol. 5, no. 11, pp. 1-10, 2024.

[4] Y. Xu, X. Liu, X. Cao, C. Huang, E. Liu, S. Qian, and J. Zhang, "Artificial intelligence: A powerful paradigm for scientific research," The Innovation, vol. 2, no. 4, 2021.

[5] S. Mazumder, Numerical Methods for Partial Differential Equations: Finite Difference and Finite Volume Methods, Academic Press, 2015.

[6] S. P. Hong, "Different numerical techniques, modeling and simulation in solving complex problems," Journal of Machine and Computing, pp. 58–68, 2023.

[7] A. Habib, A. A. Houri, M. T. Junaid, and S. Barakat, "A systematic and bibliometric review on physics-based neural networks applications as a solution for structural engineering partial differential equations," Structures, vol. 69, p. 107361, Nov. 2024.

[8] A. Tezuka, "Finite element and finite difference methods," Springer Handbook of Metrology and Testing, pp. 1033–1060, 2011.

[9] G. X. W., Y. M. Zhu, and T. Pan, "Finite line method for solving high-order partial differential equations in science and engineering," Partial Differ. Equ. Appl. Math., vol. 7, p. 100477, 2023.

[10] N. L. Rane, M. Paramesha, S. P. Choudhary, and J. Rane, "Machine Learning and Deep Learning for Big Data Analytics: A Review of Methods and Applications," Partners Universal International Innovation Journal, vol. 2, no. 3, pp. 172–197, 2024.

[11] N. Rane, S. Choudhary, and J. Rane, "Machine Learning and Deep Learning: A Comprehensive Review on Methods, Techniques, Applications, Challenges, and Future Directions," Techniques, Applications, Challenges, and Future Directions, May 31, 2024.

[12] I. H. Sarker, "Deep learning: A comprehensive overview on techniques, taxonomy, applications and research directions," SN Computer Science, vol. 2, no. 6, p. 420, 2021.

[13] M. Kommineni, "Investigating High-Performance Computing Techniques for Optimizing and Accelerating AI Algorithms Using Quantum Computing and Specialized Hardware," Int. J. Innov. Sci. Eng., vol. 16, no. 1, pp. 66–80, 2022.

[14] A. Mzukwa, "Exploring Next-Generation Architectures for Advanced Computing Systems: Challenges and Opportunities," J. Adv. Comput. Syst., vol. 4, no. 6, pp. 9–18, 2024.

[15] R. K. Raj, C. J. Romanowski, J. Impagliazzo, S. G. Aly, B. A. Becker, J. Chen, and N. Thota, "High performance computing education: Current challenges and future directions," in Proc. Working Group Reports Innovation and Tech. in Comput. Sci. Educ., pp. 51–74, 2020.

[16] J. Hutson, Ed., The Rise of AI in Academic Inquiry, IGI Global, 2024.

[17] A. Cohen, X. Shen, J. Torrellas, J. Tuck, Y. Zhou, S. Adve, and Y. Zhu, "Inter-disciplinary research challenges in computer systems for the 2020s," 2018.

[18] T. Pasupathipillai, "Data-driven discovery of the mechanism of systems described by partial differential equations," 2023.

[19] X. Chen, K. Zhang, Z. Ji, X. Shen, P. Liu, L. Zhang, and J. Yao, "Progress and Challenges of Integrated Machine Learning and Traditional Numerical Algorithms: Taking Reservoir Numerical Simulation as an Example," Mathematics, vol. 11, no. 21, p. 4418, 2023.

[20] S. Talib, "Computational Engineering Advancements: General Review of Mathematical Modelling in Computer Engineering Applications," Al-Rafidain J. Eng. Sci., pp. 51–71, 2024.

[21] F. Hasan, H. Ali, and H. A. Arief, "From Mesh to Neural Nets: A Multi-Method Evaluation of Physics-Informed Neural Networks and Galerkin Finite Element Method for Solving Nonlinear Convection-Reaction-Diffusion Equations," arXiv preprint arXiv:2411.09704, 2024.

[22] S. Chen, Z. Liu, W. Zhang, and J. Yang, "A Hard-Constraint Wide-Body Physics-Informed Neural Network Model for Solving Multiple Cases in Forward Problems for Partial Differential Equations," Appl. Sci., vol. 14, no. 1, p. 189, 2023.

[23] J. Ukwaththa, S. Herath, and D. P. P. Meddage, "A review of machine learning (ML) and explainable artificial intelligence (XAI) methods in additive manufacturing (3D printing)," Mater. Today Commun., p. 110294, 2024.

[24] W. D. Henshaw and D. W. Schwendeman, "An adaptive numerical scheme for high-speed reactive flow on overlapping grids," J. Comput. Phys., vol. 191, no. 2, pp. 420–447, 2003.

[25] S. T. Boppiniti, "Big Data Meets Machine Learning: Strategies for Efficient Data Processing and Analysis in Large Datasets," Int. J. Creative Res. Comput. Technol. Design, vol. 2, no. 2, 2020.

[26] M. M. Shior, B. C. Agbata, W. Obeng-Denteh, P. A. Kwabi, I. G. Ezugorie, S. Marcos, et al., "Numerical solution of partial differential equations using MATLAB: Applications to one-dimensional heat and wave equations," Scientia Africana, vol. 23, no. 4, pp. 243-254, 2024.

[27] C. Yip, L. Seol, and X. Z. Hon, "A Step-by-Step Approach to Partial Differential Equations," Fusion of Multidisciplinary Research, An Int. J., vol. 3, no. 1, pp. 302-315, 2022.

[28] M. Nadeem and S. W. Yao, "Solving the fractional heat-like and wave-like equations with variable coefficients utilizing the Laplace homotopy method," Int. J. Numer. Methods Heat Fluid Flow, vol. 31, no. 1, pp. 273-292, 2021.

[29] J. Okwuwe and O. E. Oduselu-Hassan, "AI-Augmented Finite Difference Methods for Solving PDEs," Asian J. Math. Comput. Res., vol. 31, no. 4, pp. 56-67, 2024.

[30] Y. Wang, K. Wang, and C. Zhang, "Applications of artificial intelligence/machine learning to high-performance composites," Compos. Part B: Eng., p. 111740, 2024.

[31] A. Shittu, "Enhancing Pipeline Simulations through Artificial Intelligence and Machine learning: A Smart Proxy Modelling Approach," M.S. thesis, West Virginia University, 2024.

[32] J. Okwuwe and O. E. Oduselu-Hassan, "AI-Augmented Finite Difference Methods for Solving PDEs: Advancing Numerical Solutions in Mathematical Modeling," Asian J. Math. Comput. Res., vol. 31, no. 4, pp. 56-67, 2024.

[33] R. Yang, J. Hu, Z. Li, J. Mu, T. Yu, J. Xia, et al., "Interpretable machine learning for weather and climate prediction: A review," Atmos. Environ., p. 120797, 2024.

[34] L. Chen, B. Han, X. Wang, J. Zhao, W. Yang, and Z. Yang, "Machine learning methods in weather and climate applications: A survey," Appl. Sci., vol. 13, no. 21, p. 12019, 2023.

[35] A. C. Lorenc, "Analysis methods for numerical weather prediction," Q. J. R. Meteorol. Soc., vol. 112, no. 474, pp. 1177-1194, 1986.

[36] M. M. Chertkov, "Mixing artificial and natural intelligence: from statistical mechanics to ai and back to turbulence," J. Phys. A: Math. Theor., vol. 57, no. 33, p. 333001, 2024.

[37] W. E. Schiesser, Method of lines PDE analysis in biomedical science and engineering, John Wiley & Sons, 2016.

[38] M. Craig, A. L. Jenner, B. Namgung, L. P. Lee, and A. Goldman, "Engineering in medicine to address the challenge of cancer drug resistance: from micro-and nanotechnologies to computational and mathematical modeling," Chem. Rev., vol. 121, no. 6, pp. 3352-3389, 2020.

[39] J. Kaur, "AI-Augmented Medicine: Exploring the Role of Advanced AI Alongside Medical Professionals," in Advances in Computational Intelligence for the Healthcare Industry 4.0, IGI Global, 2024, pp. 139-159.

[40] A. Malehmir, R. Durrheim, G. Bellefleur, M. Urosevic, C. Juhlin, D. J. White, et al., "Seismic methods in mineral exploration and mine planning: A general overview of past and present case histories and a look into the future," Geophysics, vol. 77, no. 5, pp. WC173-WC190, 2012.

[41] J. Krzywanski, M. Sosnowski, K. Grabowska, A. Zylka, L. Lasek, and A. Kijo-Kleczkowska, "Advanced computational methods for modeling, prediction and optimization—a review," Materials, vol. 17, no. 14, p. 3521, 2024.

[42] A. Goel, A. K. Goel, and A. Kumar, "The role of artificial neural network and machine learning in utilizing spatial information," Spatial Inf. Res., vol. 31, no. 3, pp. 275-285, 2023.

[43] S. Salcedo-Sanz, J. L. Rojo-Álvarez, M. Martínez-Ramón, and G. Camps-Valls, "Support vector machines in engineering: an overview," Wiley Interdiscip. Rev. Data Mining Knowl. Discov., vol. 4, no. 3, pp. 234-267, 2014.

[44] M. Frank, D. Drikakis, and V. Charissis, "Machine-learning methods for computational science and engineering," Computation, vol. 8, no. 1, p. 15, 2020.

[45] A. K. Runchal and M. M. Rao, "CFD of the Future: Year 2025 and Beyond," in 50 Years of CFD in Engineering Sciences: A Commemorative Volume in Memory of D. Brian Spalding, pp. 779-795, 2020.

[46] D. Panchigar, K. Kar, S. Shukla, R. M. Mathew, U. Chadha, and S. K. Selvaraj, "Machine learning-based CFD simulations: a review, models, open threats, and future tactics," Neural Comput. Appl., vol. 34, no. 24, pp. 21677-21700, 2022.

[47] M. Majchrzak, K. Marciniak-Lukasiak, and P. Lukasiak, "A survey on the application of machine learning in turbulent flow simulations," Energies, vol. 16, no. 4, p. 1755, 2023.

[48] A. Beck and M. Kurz, "A perspective on machine learning methods in turbulence modeling," GAMM-Mitteilungen, vol. 44, no. 1, p. e202100002, 2021.

[49] K. Bian and R. Priyadarshi, "Machine learning optimization techniques: a Survey, classification, challenges, and Future Research Issues," Arch. Comput. Methods Eng., pp. 1-25, 2024.

[50] Y. Karulkar, A. Shah, and R. Naik, "AI-Powered Business Evolution: Transformative Strategies for Success of Evolving Industries," in Creating AI Synergy Through Business Technology Transformation, IGI Global, 2025, pp. 39-72.

[51] V. Kachitvichyanukul, "Comparison of three evolutionary algorithms: GA, PSO, and DE," Industrial Engineering and Management Systems, vol. 11, no. 3, pp. 215-223, 2012.

[52] S. Das, A. Abraham, and A. Konar, "Particle swarm optimization and differential evolution algorithms: technical analysis, applications and hybridization perspectives," Advances of Computational Intelligence in Industrial Systems, pp. 1-38, 2008.

[53] B. Xin, J. Chen, J. Zhang, H. Fang, and Z. H. Peng, "Hybridizing differential evolution and particle swarm optimization to design powerful optimizers: a review and taxonomy," IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 42, no. 5, pp. 744-767, 2011.

[54] G. L. Pappa, G. Ochoa, M. R. Hyde, A. A. Freitas, J. Woodward, and J. Swan, "Contrasting meta-learning and hyper-heuristic research: the role of evolutionary algorithms," Genetic Programming and Evolvable Machines, vol. 15, pp. 3-35, 2014.

[55] V. A. de Santiago Junior, E. Özcan, and V. R. de Carvalho, "Hyper-heuristics based on reinforcement learning, balanced heuristic selection and group decision acceptance," Applied Soft Computing, vol. 97, p. 106760, 2020.

[56] G. Csurka, R. Volpi, and B. Chidlovskii, "Unsupervised domain adaptation for semantic image segmentation: a comprehensive survey," arXiv preprint arXiv:2112.03241, 2021.

[57] I. Papadimitriou, I. Gialampoukidis, S. Vrochidis, and I. Kompatsiaris, "AI methods in materials design, discovery and manufacturing: A review," Computational Materials Science, vol. 235, p. 112793, 2024.

[58] S. Badini, S. Regondi, and R. Pugliese, "Unleashing the power of artificial intelligence in materials design," Materials, vol. 16, no. 17, p. 5927, 2023.

[59] T. M. Alabi, E. I. Aghimien, F. D. Agbajor, Z. Yang, L. Lu, A. R. Adeoye, and B. Gopaluni, "A review on the integrated optimization techniques and machine learning approaches for modeling, prediction, and decision making on integrated energy systems," Renewable Energy, vol. 194, pp. 822-849, 2022.

[60] N. Abbasi, F. N. U. Nizamullah, and S. Zeb, "AI in healthcare: integrating advanced technologies with traditional practices for enhanced patient care," BULLET: Jurnal Multidisiplin Ilmu, vol. 2, no. 3, pp. 546-556, 2023.

[61] S. Zeb, F. N. U. Nizamullah, N. Abbasi, and M. Fahad, "AI in healthcare: revolutionizing diagnosis and therapy," International Journal of Multidisciplinary Sciences and Arts, vol. 3, no. 3, pp. 118-128, 2024.

[62] W. Olabiyi, "Assessment in financial fraud: the role of AI-powered risk detection," 2024.

[63] M. Alabi and A. W. Ang, "AI-Driven Financial Risk Management: Detecting Anomalies and Predicting Market Trends," 2024.

[64] W. Hilal, S. A. Gadsden, and J. Yawney, "Financial fraud: a review of anomaly detection techniques and recent advances," Expert Systems With Applications, vol. 193, p. 116429, 2022.

[65] G. Yenduri, M. Ramalingam, G. C. Selvi, Y. Supriya, G. Srivastava, P. K. R. Maddikunta, and T. R. Gadekallu, "GPT (Generative Pre-Trained Transformer) – a comprehensive review on enabling technologies, potential applications, emerging challenges, and future directions," IEEE Access, 2024.

[66] D. Lee, J. Lee, and D. Shin, "GPT Prompt Engineering for a Large Language Model-Based Process Improvement Generation System," Korean Journal of Chemical Engineering, pp. 1-24, 2024.

[67] S. Frincu and M. Frincu, "Enabling interdisciplinary learning and research through AI-driven transliteration of historical documents: A case study proposal from digital humanities," The International Journal of Humanities Education, vol. 23, no. 1, p. 1, 2024.

[68] S. V. Mahadevkar, S. Patil, K. Kotecha, L. W. Soong, and T. Choudhury, "Exploring AI-driven approaches for unstructured document analysis and future horizons," Journal of Big Data, vol. 11, no. 1, p. 92, 2024.

[69] J. C. Jeffri and A. Tamizhselvi, "Enhancing Music Discovery: A Real-Time Recommendation System using Sentiment Analysis and Emotional Matching with Spotify Integration," in 2024 8th International Conference on Electronics, Communication and Aerospace Technology (ICECA), 2024, pp. 1365-1373.
[70] U. L. Tupe, A. Kulkarni, G. Nimbokar, P. Mahajan, and N. Raut, "AI based Song Recommendations System," Grenze Int. J. Eng. Technol. (GIJET), vol. 10, 2024.
[71] L. P. Fernandes, P. Kharate, and B. Singh, "The Future of High Performance Computing in Biomimetics and Some Challenges," in High Performance Computing in Biomimetics: Modeling, Architecture and Applications, Singapore: Springer Nature Singapore, 2024, pp. 287-303.
[72] E. Maeda, D. Teruya, and H. Nakajo, "Preliminary evaluation of cache coherent interconnect for Reconfigurable Virtual Accelerator (ReVA)," IEICE Tech. Rep., vol. 121, no. 344, pp. 132-137, 2022.
[73] K. Georgopoulos, G. Chrysos, P. Malakonakis, A. Nikitakis, N. Tampouratzis, A. Dollas, and Y. Papaefstathiou, "An evaluation of Vivado HLS for efficient system design," in Proc. 2016 Int. Symp. ELMAR, Sep. 2016, pp. 195-199, IEEE.
[74] P. Shantharama, A. S. Thyagaturu, and M. Reisslein, "Hardware-accelerated platforms and infrastructures for network functions: A survey of enabling technologies and research studies," IEEE Access, vol. 8, pp. 132021-132085, 2020.
[75] M. Capra, B. Bussolino, A. Marchisio, G. Masera, M. Martina, and M. Shafique, "Hardware and software optimizations for accelerating deep neural networks: Survey of current trends, challenges, and the road ahead," IEEE Access, vol. 8, pp. 225134-225180, 2020.
[76] M. Yazdi, "Application of Quantum Computing in Reliability Analysis," in Advances in Computational Mathematics for Industrial System Reliability and Maintainability, Cham: Springer Nature Switzerland, 2024, pp. 139-154.
[77] D. Sandua, Deciphering Quantum Mechanics, David Sandua, 2024.
[78] N. Jeyaraman, M. Jeyaraman, S. Yadav, S. Ramasubramanian, and S. Balaji, "Revolutionizing Healthcare: The Emerging Role of Quantum Computing in Enhancing Medical Technology and Treatment," Cureus, vol. 16, no. 8, e67486, 2024.
[79] R. K. Malviya, R. R. Danda, K. K. Maguluri, and B. V. Kumar, "Neuromorphic Computing: Advancing Energy-Efficient AI Systems through Brain-Inspired Architectures," Nanotechnology Perceptions, pp. 1548-1564, 2024.
[80] G. Indiveri and Y. Sandamirskaya, "The importance of space and time for signal processing in neuromorphic agents: the challenge of developing low-power, autonomous agents that interact with the environment," IEEE Signal Processing Magazine, vol. 36, no. 6, pp. 16-28, 2019.