International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7455
Article Received: 15 May 2023 Revised: 05 July 2023 Accepted: 30 July 2023

Machine Learning Based Fluid-Transportation Monitoring and Controlling

Kiran Bhoite[1], Dr. S. M. Bhosle[2], Riddhi Mirajkar[3], Rahul More[4] , Sachin Kolekar[5]
[1]Department of Mechanical Engineering, VIIT, Pune, India
Pune Institute of Computer Technology, Pune, India
e-mail: klbhoite@gmail.com
[2]Department of Mechanical Engineering, VPKBIET, Baramati, India
e-mail: hod.mech@vpkbiet.org
[3]Department of Information Technology, VIIT, Pune, India
e-mail: riddhi.mirajkar@viit.ac.in
[4-5]Department of computer science Engineering, MIT ADT University, Pune, India
e-mail: rahul.p.more@mitadtuniversity.edu.in, sachin.kolekar@mitadtuniversity.edu.in

Abstract— The discipline of fluid mechanics is developing quickly, propelled by previously unheard-of data volumes from experiments, field measurements, and expansive simulations at various spatiotemporal scales. The field of machine learning (ML) provides a plethora of methods for gleaning insights from data that can be used to inform our understanding of the fluid dynamics at play. As an added bonus, ML algorithms can be used to automate duties associated with flow control and optimization, while also enhancing domain expertise. This article provides a review of the background, current state, and potential future applications of ML in fluid mechanics. We provide an introduction to the most fundamental ML approaches and describe their applications to the study, modelling, optimization, and management of fluid flows. From the standpoint of scientific inquiry, which treats data as an integral aspect of modelling, experiments, and simulations, the benefits and drawbacks of these approaches are discussed. Since ML provides a robust information-processing framework, it can supplement and potentially revolutionize conventional approaches to fluid mechanics study and industrial applications.

Keywords- Machine Learning, Artificial Intelligence, Fluid Transportation, Optimization.

I. INTRODUCTION

Studies of fluids cover a broad variety of length scales, from picoseconds to hours or more, and time scales, from the quantum to the continuous. There have historically been separate teams to study phenomena at each scale. Because of advancements in high- performance computer architectures, multiscale simulation methodologies are now a reality, uniting formerly siloed areas of study on a single platform. Understanding fluid behavior requires physics-based descriptions since the electrical and atomic properties of the substance often affect the overall behavior. Thanks to developments in materials science, precise atomic-scale experiments can now be carried out in a lab, and real-world data is continually being provided by industrial and large-scale studies to inform the research.

1.1. DATA SCIENCE

Computer science has undergone multiple paradigm transformations, beginning with empirical techniques and progressing through the model-based theoretical paradigm and into the computational third paradigm. Data collection has advanced beyond our understanding of the underlying systems. In order to go above its traditional predecessors, the present data-driven fourth paradigm is founded on the development of trustworthy prediction and discovery-based data mining techniques on huge datasets [1]. Traditional models of scientific progress mathematical modeling, experiments, and computer simulations are supported by the fourth paradigm. There are many different types of data that can be used to visually describe a phenomenon. These include continuous data like vectors and tensors, discrete data like words, data represented by weighted graphs, and data in the form of images and movies. Modeling thermodynamic properties requires picking and balancing data from a wide variety of sources, including experiments and simulations [4].

1.2. APPLYING MACHINE LEARNING AND AI TO FLUID DYNAMICS STUDYING

The emergence of artificial intelligence has inspired an avalanche of articles that seek to bridge the gap between cutting-edge algorithm design and intuitive human comprehension [5]. The two main types of learning are supervised learning, in which predictions are made using data that has already been labeled, and unsupervised learning, in which data that has not been labeled is used. In supervised learning, the connection between inputs and outputs is learned with the help of training data. In order to begin unsupervised

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7455
***Article Received**: 15 May 2023 **Revised:** 05 July 2023 **Accepted:** 30 July 2023*

learning, one must first explore all possible input data configurations [6]. Others consider Reinforcement Learning (RI) to be a subset of ML distinct from the other two. To improve its performance, an RL model doesn't need to be fed data in advance but instead creates its own data in real time and "self-trains" [7]. On the other hand, one could see ML as a novel approach to solving classic problems in fluid mechanics [8]. In addition, it may explain the predictions and design explainable techniques [11] by capturing data behavior while reducing extraneous pieces. It is common practice for inferred algorithms to use their own predictions from the same dataset to verify their accuracy [12], following a decision procedure. In traditional numerical approaches, the accuracy of predictions is often compromised in favor of computational efficiency. The high computational cost means that simulations can only be done on relatively simple systems for short times, producing findings that are comparable to those obtained in experiments. The advancement of material discovery can be driven by their mutually beneficial applications. However, just because you have access to a massive amount of data does not mean that it is in a useable form. Due to factors such as the large dimensionality of the space, geometrical repercussions, boundary conditions, and the nonlinear nature of fluid mechanics, ML often finds itself working with sparse data. Parallel to the progress achieved in statistical learning, new methods for recovering symbolic expressions from data have been developed. These methods don't require any preexisting familiarity with the inferred system. The possibility of describing information in terms of physical laws has become a practical reality. [19]. Below, we highlight the most important findings from these studies. The purpose of this research is twofold:

1. To compare the proposed Machine Learning- based Monitoring and Control of Fluid Transportation System to existing algorithms and classifiers, and
2. To evaluate the effectiveness of these methods

The final steps in the model's construction are described here. In Part II, we examine the issues and relevant works. After that, in Section III, we propose a machine- learning-based system for tracking and managing fluid transit. More information on the suggested model is provided in Section IV. In Section V, you will learn about the system's pros and cons. Comparison of the new method to the old is provided in Section VI.

II. RELATED REVIEW

2.1 Existing Work

There are several apps that can be used with the Internet of Things; however, only a small portion of these applications are currently accessible to the general population [11]. The Internet of Things (IoT) is supported by a variety of different pillars of innovation, one of which is the relatively recent consolidation of a large number of RFID inventions into a single set of products. This is just one example. The Internet of Things offers an advantage over the status quo in a number of different areas of industrial management, such as environmental monitoring, smart cities, smart business/inventory and product management, etc., [12].

2.2 ANALYSES AND INTERPRETATIONS OF RECENT FLUID RESEARCH AND ML

New assessments and perspectives on the overlap between ML and fluids have been offered in a number of recent studies. Brunton et al. [20] offer a historical perspective on fluid mechanics, situating recent developments within the context of longer-term trends. Brenner et al. [8] note that different ML applications require varying amounts of quantitative and qualitative training data. When handling the basics of fluid mechanics, it is advised that ML be used in conjunction with human intuition and physical reasoning. The decisions that ML makes must adhere to physical principles if it is to be trusted. Scientists are recommended to pick the right model/problem and available data, figure out the right architecture, create loss functions to assess performance and guide the learning process, and ultimately, apply an optimization approach to minimize the loss function over the training data [21]. Furthermore, the data scarcity and uncertainty that characterize many applications utilizing the thermo physical features of fluids necessitates a physical understanding of how to cope with these issues. As an analytical tool, ML can help us learn more about the physical world and improve our understanding of ML models [22]. With an emphasis on multiphase flows controlled by sensor data, the review of Arief et al. [23] offers technical recommendations on how to characterize fluid flow in pipes. Traditional computing approaches like the speed-of-sound estimate and the Joule-Thomson coefficient are frequently used in conjunction with ML algorithms. One of the most common uses of ML is in the study of turbulence models, wherein novel methods to parameterize unresolved scales in complex flow configurations at high Reynolds numbers have been explored. There are real-world uses for growing computing power, more advanced machine learning algorithm techniques, and the availability of large datasets. It would be helpful to have faster, higher-resolution, and more accurate sensors for collecting data in the field, as well as unique data compression algorithms for dealing with enormous datasets [10].

As it is, a large variety of classifiers are used in the field of fluid transportation for image processing and retrieval systems. The accuracy and speed with which an operation is

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7455
***Article Received**: 15 May 2023 **Revised:** 05 July 2023 **Accepted:** 30 July 2023*

completed depends on the quality of the various classifiers that can be applied to it. The following table summarizes the several classifiers that can be used to divide information into positive and negative categories.

2.3 THE ALGORITHM IN FLUID DYNAMICS

After that, we will go over the most popular ML algorithms that have been effectively implemented in fluid research. We emphasize that this is by no means an exhaustive list of the algorithmic implementations utilized in fluid (or, more generally, material) research, but rather a representative sample. Figure depicts these statistical relationships visually. Since Deep, Convolutional, and Recurrent Neural Network techniques need sophisticated implementations and can be considered as a separate field of research for large datasets and/or graphical data processing, we did not include them in this study. It is anticipated that DNNs will play a significant role in the development of molecular representations in chemical informatics.

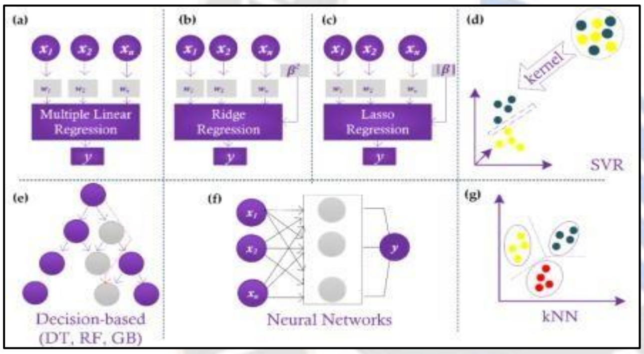

Figure1: Different ML Algorithms

Figure 1 shows Artificial intelligence (AI) algorithmic indications in fluid dynamics study. a) Ridge Regression, b) Lasso Regression, c) Support Vector Regression, d) Decision Tree, and e) Multiple Linear Regression. The tree-model used in (f) Neural Network for Figure is also the basis for the popular methods of Random Forest and Gradient Boosting. Incorporating machine learning algorithms into fluid dynamics study— an illustrative list.

No	References	Algorithm	Algorithm Type	Learning Type
1	[17]	AdaBoost	Ensemble	Supervised
2	[18]	Bayesian Network Seasonal Autoregressive Integrated Moving Average (BN-SARIMA)	Bayesian	Supervised
3	[19–21]	Convolutional Neural Network (CNN) and Deep CNN (DCNN)	Deep Learning	Reinforcement
4	[22]	Coupled Hidden Markov Model (CHMM)	Markov Model	Reinforcement
5	[23]	Decision Tree	Decision Trees	Supervised
6	[12,24]	Deep Belief Networks (DBN)	Deep Learning	Reinforcement
7	[25]	Deep Recurrent Attention Model (DRAM)	Recursive Neural Networks-Deep Learning	Reinforcement
8	[26]	Fuzzy C-Means (FCM)	Clustering	Unsupervised
9	[18,23,27–30]	Feed Forward Neural Networks (FF-NN)	Artificial Neural Networks	Supervised
10	[20]	Fully Connected Networks (FCN)	Deep Learning	Reinforcement
11	[31]	Stacked Auto Encoder (SAE) with Greedy Layer-wise training	Deep Learning	Reinforcement, Unsupervised
12	[32]	Inception Neural Networks	Deep Learning	Reinforcement
13	[12,33,34]	K-Means	Clustering	Unsupervised
14	[24,29,35]	*k*-Nearest Neighbor (*k*-NN)	Instance Based	Supervised
15	[23]	Logistic Regression	Regression	Supervised
16	[36]	Markov Decision Process (MDP)	Discrete Time Stochastic Control	Reinforcement
17	[14]	Markov Random Field (MRF)	Markov Model	Unsupervised
18	[18]	Nonlinear Autoregressive eXogenous model (NARX)	Recursive Neural Networks-Deep Learning	Reinforcement
19	[36]	Q-Learning	Stochastic	Reinforcement

Figure 2: A detailed comparison of basic machine learning approaches

2.4 MACHINE LEARNING'S CHALLENGES AND OPPORTUNITIES IN FLUID DYNAMICS

While compared to more common uses of ML, such image identification and advertising, the difficulties encountered when dealing with fluid dynamics are unique. The analysis of fluid flows frequently necessitates the accurate quantification of underlying physical mechanisms. In addition, fluid flows display multiscale phenomena that are still mostly unclear and difficult to manage. However, common ML methods may lack the flexibility needed to deal with the nonlinearities and numerous spatiotemporal scales prevalent in unsteady flow fields. In addition, many well- known ML applications, like playing Go, rely on low-cost system evaluations and a thorough classification of the learning process. However, this is not the case when dealing with fluids, where it can be difficult to repeat or automate experiments and where simulations may necessitate the use of large-scale supercomputers running for long periods of time. Algorithms like reinforcement learning

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7455
***Article Received**: 15 May 2023 **Revised:** 05 July 2023 **Accepted:** 30 July 2023*

(RL) are commonly employed in autonomous driving and aircraft, and ML has also proven crucial in robotics. Many robot applications use fluids, however, it does not appear that fluid dynamics' complexities are now a key issue in their design. Solutions that mimic natural shapes and processes are commonplace, much like they were in the early days of aviation (see the sidebar titled Learning Fluid Mechanics: From Living Organisms to Machines).

When designing robotic systems, we believe a thorough comprehension and utilization of fluid mechanics will become crucial when concerns such as energy consumption and dependability in complex flow situations emerge. Because of the potential for a change in the system's nature when flow dynamics are actively or passively manipulated for an engineering goal, relying on data from uncontrolled systems to make predictions is risky business in the context of flow control. However, while flow data may be abundant in some respects, such as spatial resolution, it may be lacking in others, such as the cost of conducting parametric studies. In addition, flow data can be extremely varied, necessitating caution when deciding on an LM. Furthermore, many fluid systems are non stationary, and it may be too costly to get statistically convergent findings even for stationary flows.

III. PROBLEM STATEMENT

Machine learning and the IoT are slowly making their way into the field of fluid mechanics because of their revolutionary success on many difficult problems, such as computer vision and natural language processing. Despite all the potential and scope around machine learning, many experts remain skeptical about its usefulness. Both groups are interested in learning more about the benefits and drawbacks of machine learning and the most effective ways to integrate it into their current research and development practices. While training a machine learning model for a specific task has become significantly easier in recent years, developing a model that can compete with or even exceed state-of-the-art numerical techniques or physics-based models is still a significant issue. As modern machine learning and the Internet of Things rely heavily on a model's generalizability, interpretability, and explainability, introducing partial physics into the pipeline tends to improve all three. Due to the poor performance of the remaining 32% of manually operated loops, safety is the leading motivation for highly advanced control systems. Because of this, it is more crucial than ever to employ a complex controller in order to ascertain the optimal functioning of a system in the current environment.

IV. PROPOSED METHODOLOGY

The primary goal is to upgrade the entire factory's wiring to a more modern, alert system that employs smart objects and intelligent communication for real-time monitoring and command. In this study, we investigate how IoT can serve as a catalyst for the adoption of multiband communication inside corporate settings. In order for devices to talk to one another wirelessly, they must be connected through the IoT. Internet of Things is in competition with related technologies like Lora and Sigfox. The former is similar to the latter in that it offers excellent indoor and outdoor coverage, low latency, low connectivity costs, low power consumption, and an efficient network design. The Internet of Things reduces the impact of issues like bandwidth restrictions, interference, and congestion in the public radio frequencies. Because of the 4G network's widespread radio coverage, the IoT may reap the benefits of the preexisting infrastructure to the fullest extent possible. The frequency range employed also allows for higher penetration below or within buildings [7]. This RS485-based worldwide IoT industrial gateway can collect data from many serial Modbus devices (ASCII, RTU) simultaneously. Industrial applications send and receive data from the IoT using several bands to provide fair distribution of available bandwidth across the many components of the CIM pyramid (WSN, Machines, SCADA, ERP, and EMS).

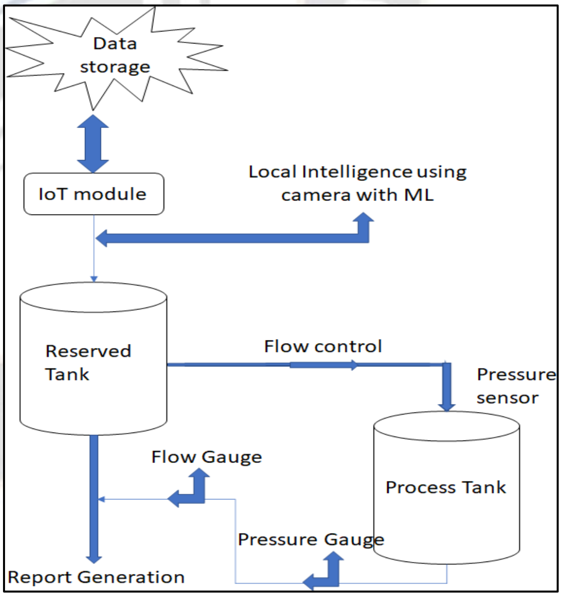

Figure 3**:** Flow of proposed work

Figure 3 illustrates the connection between the IoT module and the experimental apparatus. The station's pressure and flow rate transmitter is locally controlled by the controller via SCADA, with data being sent to an IoT module. Data from the pressure transmitter is identified as IP1 and data from the flow meter as IP4 in the IoT front-end operator interface. The studies

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7455
***Article Received**: 15 May 2023 **Revised:** 05 July 2023 **Accepted:** 30 July 2023*

only involve the remote monitoring and manipulation of two variables: pressure at the boosting station and flow rate at the final delivery station. The IoT module receives signals from both the pressure transmitter (through AC1's analogue current input port) and the flow transmitter (through AC4's analogue current input port), and then uploads them to the cloud for later analysis. Digital output port DO2 is triggered if the emergency power off switch is pressed. If the local intelligence at the field station and the interfaced pump are turned off, both are immediately disconnected, thanks to this digital output relay.

5. Advantages of using proposed approach

The primary benefit is that developed local intelligence is able to carry out better control actions; however, this is only the case when the parameter changes fall within the threshold limit; once it exceeds the monitoring range, the developed local intelligence is unable to provide appropriate decisions. The introduction of IoT allows for the controller performances and local control unit control signals to be recorded and evaluated in the cloud, which enables an immediate remedy to be provided before it can result in disastrous circumstances.

CONCLUSION AND FUTURE PERSPECTIVES

Even though ML algorithms have just recently gained popularity, they are clearly defined and have widespread support from the scientific community. The literature review conducted for this study indicates that current investments in fluid dynamics and mechanics applications are focused on Deep Neural Network applications on traditional transportation challenges. Our results, however, show that another method exists for easing the implementation of ML in fluid dynamics. As they provide a fast and accurate framework that can traverse any fluid application that infers data, non-linear, tree-based algorithms will continue to be the focus of research. As these forms of artificial intelligence and machine learning become standard computational aids for simulations and experimental investigations, we foresee a time when their use will be taken for granted rather than highlighted. More and more data mean that modern artificial intelligence (AI) and machine learning (ML) techniques can be applied to fluid mechanics, leading to promising new developments in this area. The possibility for significant new developments in fluid mechanics stems from the availability of data and its connection with experimental, theoretical, empirical, simulation, and innovative ML approaches. Therefore, it is essential that all databases continue to be made available for scholarly research. The popularity of synergistic platforms is only predicted to grow, and data science is quickly becoming an essential part of contemporary investigation.

REFERENCES

[1] Agrawal, A.; Choudhary, A. Perspective: Materials Informatics and Big Data: Realization of the "Fourth Paradigm" of Science in Materials Science. APL Mater. 2016, 4, 053208.
[2] Agrawal, A.; Deshpande, P.D.; Cecen, A.; Basavarsu, G.P.; Choudhary, A.N.; Kalidindi, S.R. Exploration of Data Science Techniques to Predict Fatigue Strength of Steel from Composition and Processing Parameters. Integr. Mater. Manuf. Innov. 2014, 3, 90–108.
[3] Wei, J.; Chu, X.; Sun, X.; Xu, K.; Deng, H.; Chen, J.; Wei, Z.; Lei, M. Machine Learning in Materials Science. InfoMat 2019, 1, 338–358.
[4] Paulson, N.H.; Zomorodpoosh, S.; Roslyakova, I.; Stan, M. Comparison of Statistically-Based Methods for Automated Weighting of Experimental Data in CALPHAD- Type Assessment. Calphad 2020, 68, 101728.
[5] Frank, M.; Drikakis, D.; Charissis, V. Machine-Learning Methods for Computational Science and Engineering. Computation 2020, 8, 15.
[6] Wang, T.; Zhang, C.; Snoussi, H.; Zhang, G. Machine Learning Approaches for Thermoelectric Materials Research. Adv. Funct. Mater. 2020, 30, 1906041.
[7] Alexiadis, A. Deep Multiphysics: Coupling Discrete Multiphysics with Machine Learning to Attain Self-Learning in-Silico Models Replicating Human Physiology. Artif. Intell. Med. 2019, 98, 27–34.
[8] Brenner, M.P.; Eldredge, J.D.; Freund, J.B. Perspective on Machine Learning for Advancing Fluid Mechanics. Phys. Rev. Fluids 2019, 4, 100501.
[9] Schmid, M.; Altmann, D.; Steinbichler, G. A Simulation-Data-Based Machine Learning Model for Predicting Basic Parameter Settings of the Plasticizing Process in Injection Molding. Polymers 2021, 13, 2652.
[10] Goh, G.D.; Sing, S.L.; Yeong, W.Y. A Review on Machine Learning in 3D Printing: Applications, Potential, and Challenges. Artif. Intell. Rev. 2021, 54, 63–94.
[11] Kailkhura, B.; Gallagher, B.; Kim, S.; Hiszpanski, A.; Han, T.Y.-J. Reliable and Explainable Machine-Learning Methods for Accelerated Material Discovery. npj Comput. Mater. 2019, 5, 108.
[12] Sofos, F. A Water/Ion Separation Device: Theoretical and Numerical Investigation. Appl. Sci. 2021, 11, 8548.
[13] Roscher, R.; Bohn, B.; Duarte, M.F.; Garcke, J. Explainable Machine Learning for Scientific Insights and Discoveries. IEEE Access 2020, 8, 42200–42216.
[14] Vasudevan, R.K.; Choudhary, K.; Mehta, A.; Smith, R.; Kusne, G.; Tavazza, F.; Vlcek, L.; Ziatdinov, M.; Kalinin, S.V.; HattrickSimpers, J. Materials Science in the Artificial Intelligence Age: High-Throughput Library Generation, Machine Learning, and a Pathway from Correlations to the Underpinning Physics. MRS Commun. 2019, 9, 821–838
[15] Craven, G.T.; Lubbers, N.; Barros, K.; Tretiak, S. Machine Learning Approaches for Structural and Thermodynamic Properties of a Lennard-Jones Fluid. J. Chem. Phys. 2020, 153, 104502.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7455
***Article Received**: 15 May 2023 **Revised:** 05 July 2023 **Accepted:** 30 July 2023*

[16] Sun, W.; Zheng, Y.; Yang, K.; Zhang, Q.; Shah, A.A.; Wu, Z.; Sun, Y.; Feng, L.; Chen, D.; Xiao, Z.; et al. Machine Learning-Assisted Molecular Design and Efficiency Prediction for High-Performance Organic Photovoltaic Materials. Sci. Adv. 2019, 5, eaay4275.

[17] Zhang, W.-W.; Noack, B.R. Artificial Intelligence in Fluid Mechanics. Acta Mech. Sin. 2022, 1–3. [CrossRef]

[18] Raissi, M.; Perdikaris, P.; Karniadakis, G.E. Physics-Informed Neural Networks: A Deep Learning Framework for Solving Forward and Inverse Problems Involving Nonlinear Partial Differential Equations. J. Comput. Phys. 2019, 378, 686–707.

[19] Papastamatiou, K.; Sofos, F.; Karakasidis, T.E. Machine Learning Symbolic Equations for Diffusion with Physics-Based Descriptions. AIP Adv. 2022, 12, 025004.

[20] Brunton, S.L.; Noack, B.R.; Koumoutsakos, P. Machine Learning for Fluid Mechanics. Annu. Rev. Fluid Mech. 2020, 52, 477–508.

[21] Brunton, S.L. Applying Machine Learning to Study Fluid Mechanics. Acta Mech. Sin. 2022, 1–9.

[22] Jirasek, F.; Hasse, H. Perspective: Machine Learning of Thermophysical Properties. Fluid Phase Equilib. 2021, 549, 113206. [CrossRef]

[23] Arief, H.A.; Wiktorski, T.; Thomas, P.J. A Survey on Distributed Fibre Optic Sensor Data Modelling Techniques and Machine Learning Algorithms for Multiphase Fluid Flow Estimation. Sensors 2021, 21, 2801.

[24] Pandey, S.; Schumacher, J.; Sreenivasan, K.R. A Perspective on Machine Learning in Turbulent Flows. J. Turbul. 2020, 21, 567–584.

[25] Mr. Dharmesh Dhabliya, Prof. Ojaswini Ghodkande. (2016). Prevention of Emulation Attack in Cognitive Radio Networks Using Integrated Authentication . International Journal of New Practices in Management and Engineering, 5(04), 06 - 11. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/48

[26] Botu, V.; Ramprasad, R. Learning Scheme to Predict Atomic Forces and Accelerate Materials Simulations. Phys. Rev. B Condens. Matter Mater. Phys. 2015, 92, 094306.

[27] Behler, J.; Parrinello, M. Generalized Neural-Network Representation of High- Dimensional Potential-Energy Surfaces. Phys. Rev. Lett. 2007, 98, 146401.

[28] Noé, F.; Olsson, S.; Köhler, J.; Wu, H. Boltzmann Generators: Sampling Equilibrium States of Many-Body Systems with Deep Learning. Science 2019, 365, eaaw1147.

[29] Sofos, F.; Karakasidis, T.E.; Liakopoulos, A. Fluid Flow at the Nanoscale: How Fluid Properties Deviate from the Bulk. Nanosci. Nanotechnol. Lett. 2013, 5, 457–460.

[30] Sofos, F.; Karakasidis, T.E.; Giannakopoulos, A.E.; Liakopoulos, A. Molecular Dynamics Simulation on Flows in Nano-Ribbed and Nano-Grooved Channels. Heat Mass Transf./Waerme Stoffuebertragung 2016, 52, 153–162.

[31] Mueller, T.; Hernandez, A.; Wang, C. Machine Learning for Interatomic Potential Models. J. Chem. Phys. 2020, 152, 050902.

[32] Krems, R.V. Bayesian Machine Learning for Quantum Molecular Dynamics. Phys. Chem. Chem. Phys. 2019, 21, 13392–13410.

[33] Mishin, Y. Machine-Learning Interatomic Potentials for Materials Science. Acta Mater. 2021, 214, 116980.

[34] Veit, M.; Jain, S.K.; Bonakala, S.; Rudra, I.; Hohl, D.; Csányi, G. Equation of State of Fluid Methane from First Principles with Machine Learning Potentials. J. Chem. Theory Comput. 2019, 15, 2574–2586.

[35] Peng, G.C.Y.; Alber, M.; Buganza Tepole, A.; Cannon, W.R.; De, S.; Dura-Bernal, S.; Garikipati, K.; Karniadakis, G.; Lytton, W.W.; Perdikaris, P.; et al. Multiscale Modeling Meets Machine Learning: What Can We Learn? Arch. Comput. Methods Eng. 2021, 28, 1017–1037.

[36] Tchipev, N.; Seckler, S.; Heinen, M.; Vrabec, J.; Gratl, F.; Horsch, M.; Bernreuther, M.; Glass, C.W.; Niethammer, C.; Hammer, N.; et al. TweTriS: Twenty Trillion-Atom Simulation. Int. J. High Perform. Comput. Appl. 2019, 33, 838–854.

[37] Naaz, S. ., ShivaKumar, K. B., & B. D., P. . (2023). Aggregation Signature of Multi Scale Features from Super Resolution Images for Bharatanatyam Mudra Classification for Augmented Reality Based Learning. International Journal of Intelligent Systems and Applications in Engineering, 11(3s), 224–234. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2565

[38] Mortazavi, B.; Podryabinkin, E.V.; Roche, S.; Rabczuk, T.; Zhuang, X.; Shapeev, A.V. Machine-Learning Interatomic Potentials Enable First-Principles Multiscale Modeling of Lattice Thermal Conductivity in Graphene/Borophene Heterostructures. Mater. Horiz. 2020, 7, 2359– 2367.

[39] Holland, D.M.; Lockerby, D.A.; Borg, M.K.; Nicholls, W.D.; Reese, J.M. Molecular Dynamics Pre-Simulations for Nanoscale Computational Fluid Dynamics. Microfluid. Nanofluid. 2015, 18, 461–474.

[40] Lin, C.; Li, Z.; Lu, L.; Cai, S.; Maxey, M.; Karniadakis, G.E. Operator Learning for Predicting Multiscale Bubble Growth Dynamics. J. Chem. Phys. 2021, 154, 104118.

[41] Thomas, C., Wright, S., Hernandez, M., Flores, A., & García, M. Enhancing Student Engagement in Engineering Education with Machine Learning. Kuwait Journal of Machine Learning, 1(2). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/123

[42] Wang, Y.; Ouyang, J.; Wang, X. Machine Learning of Lubrication Correction Based on GPR for the Coupled DPD–DEM Simulation of Colloidal Suspensions. Soft Matter 2021, 17, 5682–5699.

[43] Sofos, F.; Chatzoglou, E.; Liakopoulos, A. An Assessment of SPH Simulations of Sudden Expansion/Contraction 3-D Channel Flows. Comput. Part. Mech. 2022, 9, 101–115.

[44] Albano, A.; Alexiadis, A. A Smoothed Particle Hydrodynamics Study of the Collapse for a Cylindrical Cavity. PLoS ONE 2020, 15, e0239830.

[45] Aisha Ahmed, Machine Learning in Agriculture: Crop Yield Prediction and Disease Detection , Machine Learning Applications Conference Proceedings, Vol 2 2022.

[46] Bai, J.; Zhou, Y.; Rathnayaka, C.M.; Zhan, H.; Sauret, E.; Gu, Y. A Data-Driven Smoothed Particle Hydrodynamics Method for Fluids. Eng. Anal. Bound. Elem. 2021, 132, 12–32.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7455
***Article Received**: 15 May 2023 **Revised:** 05 July 2023 **Accepted:** 30 July 2023*

[47] Wang, J.; Olsson, S.; Wehmeyer, C.; Pérez, A.; Charron, N.E.; De Fabritiis, G.; Noé, F.; Clementi, C. Machine Learning of Coarse- Grained Molecular Dynamics Force Fields. ACS Cent. Sci. 2019, 5, 755–767.