Artificial Intelligence (AI) Tools for Water Purification

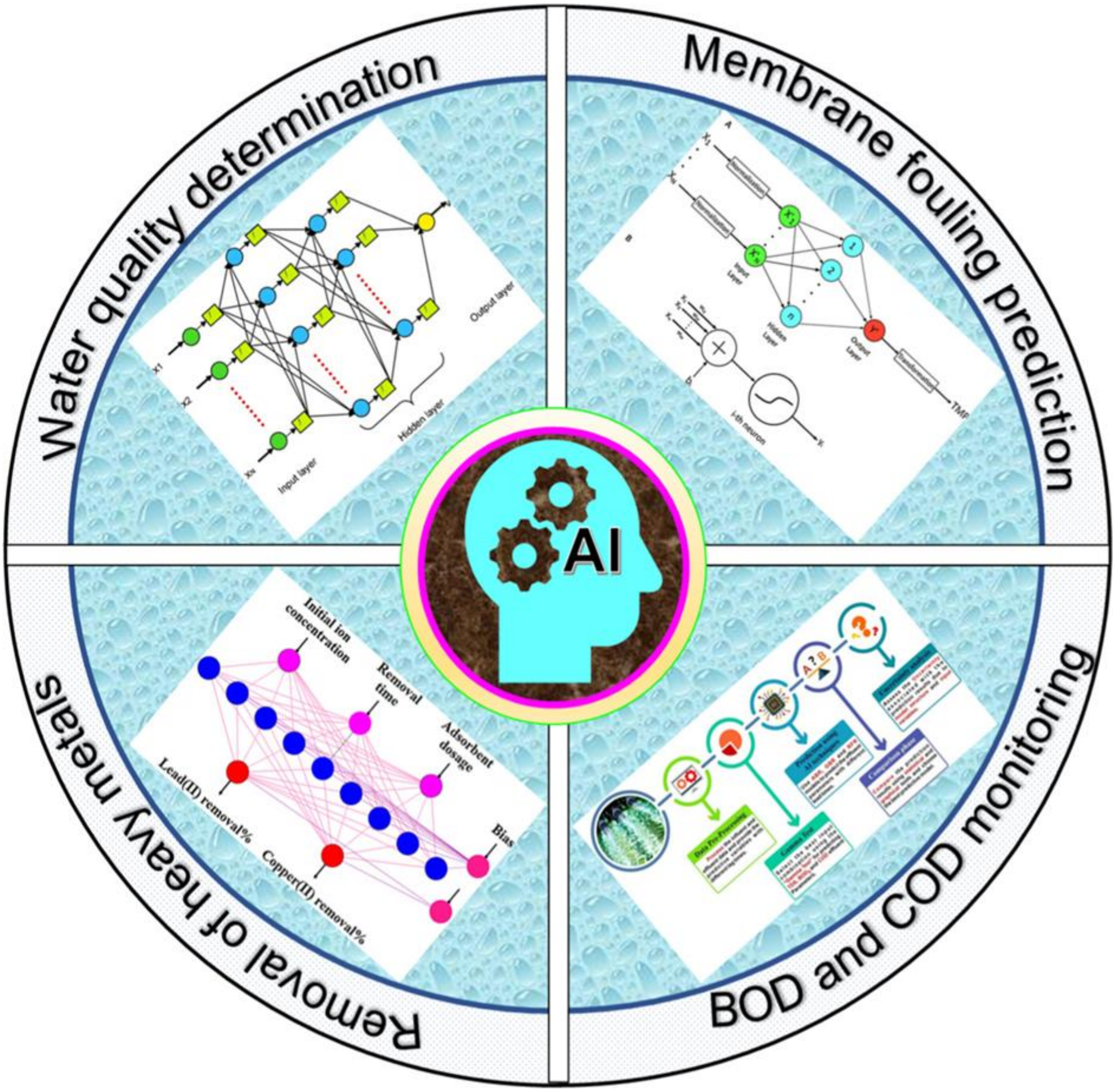
Abhishek Kumar*, Shakti Singh Yadav, Abhishek Pandey, Nilesh Kumar Tiwari and Dr. Fariya khan
Department of Biotechnology, Kanpur institute of technology rooma Uttar Pradesh-208001, India

Abstract: Artificial intelligence is an developing controlling innovative technology that can perfect real-time problems connecting many intricacies. The modelling abilities of AI techniques are quite beneficial in purification of water and also purification of wastewater. The growing demand for clean and safe water, determined by population progress and industrial development. AI has developed as a transformative technology in addressing this challenge, contribution tools that enhance water purification methods. The application of A I tools in improving water treatment methodology, monitoring water quality, and also imagining organization failures. AI technologies include multi-linear or non-linear relationships and procedure dynamics that are usually unreasonable to model by conventional methodologies. AI-driven algorithms, such as machine learning and also neural networks, are working to improve filtration developments, chemical dosing, and energy ingesting in water purification plants. These some tools allow real-time data examination from the some sensors, they allowing for active organization of water arrangements and the early uncovering of impurities. AI-powered water worth monitoring arrangements deliver continuous and accurate valuations of impurities and pathogens, dropping the support on physical testing. This ensures that water treatment facilities can maintain high ideals of water quality while minimalizing operative finances. The integration of AI tools into water purification systems has demonstrated significant potential for improving efficiency, reducing costs, and ensuring the delivery of safe drinking water. AI technology help in continues to progress of water purification, it is predictable to play essential role in addressing global water shortage and uncleanness problems. The analysis of the display of various AI technologies, The successful operation of these technologies in water treatment related applications. AI also highlights the boundaries that delay their operations in real-world water treatment organizations.

Keywords: Artificial Intelligence, Water Purification, Machine Learning, Water Quality Monitoring, Predictive Maintenance.

I. INTRODUCTION

Water, one of the necessary components to support human existence, protects three of the earth's dwellings. The availability of fresh water is just around 1% in spite of this abundance. It is anticipated that by 2030, the world's water consumption would have risen from 4200 Bm3 in 2015 to 6900 Bm3. Numerous strata, hazardous compounds with varying conformations, and rural areas are influenced by industrial and other anthropogenetic activity. Numerous techniques have been used to assess and forecast effluent quality and water fineness. including coagulation/flocculation techniques, purification, distillation, membrane percolation, biological oxygen demand (BOD), and chemical oxygen demand (COD). In order to simulate and ascertain the parametric correlations between different process variables of operative administrations, these approaches mostly use precise models and linear deteriorating processes as prediction models. These expected processes, however, are laborious, need extensive procedures, and are unable to map the significant complexity and non-linearity of administrations. Additionally, they are usually simplistic, predicated on idealistic, impractical ideas and concepts. Even while the mathematical and experimental regression models can produce predictions that are acceptable, they are unable to account for the complicated undercurrents and general nonlinear connections that are mostly present in water treatment measures.



GRAPHICAL REPRESENTATION

During water purification, several restrictions must be subtly made and addressed. For instance, in order to achieve the necessary degree of purity and sufficient deposition of pollutants, the dose of the coagulant must be effectively calculated. Outdated tests and procedures, like the jar test, which illustrates the coagulation/flocculation process of wastewater conduct plants (WWTPs) to define the ideal coagulator quantity for the process, are oppressed by the complicated chemistry of coagulants and their unpredictable interface with water scums. The procedure is time-consuming and involves the use of chemicals. Additionally, a workable solution for wastewater conduct and reuse applications is possible thanks to sheath expertise. Involuntary control systems maintain level plant activities by adjusting process parameters including flow rate, malaise, heaviness, and pH at the right time. However, conservative models that use theoretical formulations and experience links as analytical models are usually the foundation of present systems. The empirical connections are obtained from a particular experimental dataset that is not naturally suitable to other schemes due to the change in operating conditions, whereas the theoretical models are based on certain molds. In line with this, WWTPs entail complex chemical and organic processes. Due to wastewaters' diverse sources, which include industrial effluents, household discharges, and salable and public wastes, influents to WWTPs are highly variable and categorical . Their preparation, pH, and flow rate change as a result, making their procedure more difficult. Trainings have shown that the water's BOD and COD levels are the main factor used to assess WWTP performance. These factors are crucial in establishing the quality of drinkable and sustainable water, as are the levels of total suspended solids (TSS) and total nitrogen (TN). BOD and COD aid in regulating wastewater's oxygen content, which assesses aeration duration to maximize oxygen content.

Therefore, in order to effectively limit the degree of parameter inconsistency for optimal outcomes, system-specific and genuine models based on actual datasets and operating circumstances are required. AI technologies have significantly changed the engineering industry of today, known as Industry 4.0, and have prompted research in a wide range of engineering and knowledge domains, including intelligent robots, natural language processing, material design, disease diagnostics, and medicine. Technical systems that mimic natural human brain processes, such learning and interpretation, are made up of non-parametric algorithms that mimic human intelligence and specific behaviors. Artificial intelligence (AI) technologies, including genetic algorithms (GA), fuzzy logic (FL), support vector machines (SVM), deep learning (DL), and artificial neural networks (ANNs), can independently analyze, evaluate, and predict based on input data, optimize system variables, or send out warning signals to analyze parameters and adjust the output accordingly. This significantly lowers human error and increases productivity.

Common procedures including coagulation/flocculation, source water analysis, disinfection, desalination, and membrane filtration are among the current applications of AI in water purification. Due of the nonlinearity and complicated process dynamics, WWTPs also employ intelligent approaches. Water quality is often measured using ANN, adaptive neuro fuzzy inference system (ANFIS), and SVM technologies, which predict the amounts of BOD, COD, TSS, and total dissolved solids (TDS) in WWTPs. Three layers make up AI technologies, such ANNs, which are a self-adaptive nonlinear data-driven approach: 1) input layer, 2) one or more hidden layers according on the needs of the algorithm, and 3) one output layer that creates a particular output by processing the weighted average and bias in hidden layers . ANNs are made up of several combinations of computing units called neurons that are linked in a network, much like the human coordinating system. A code design flowchart for creating an ANN model is shown.

The significance and relevance of AI in water treatment procedures have not received much attention in review papers throughout the years. Li et al., for example, examined the latest advancements and uses of AI technology in drinking water treatment facilities. Similarly, advancements made by AI in the desalination process were understood. In general, earlier research has outlined the precise model phases and examined a single AI technology, like an ANN, in a particular water treatment process.

However, as of right now, there isn't a review paper that thoroughly examines the most current usage of AI in wastewater treatment and water purification procedures. The main uses of various AI technologies and process automation in various water purification and wastewater treatment processes are described in this brief summary of a recent and thorough research of the literature. With the goal of redefining the main plant processes—such as source water quality analysis and characterization, coagulation/flocculation, disinfection and desalination, membrane fouling prediction, decontamination, BOD and COD monitoring and determination—it offers comprehensive insights into the introduction of various AI techniques in the field of water treatment.

II. APPLICATION OF AI IN SOURCE WATER QUALITY DETERMINATION

In recent decades, water quality prediction approaches have been heavily researched to develop effective management strategies and enhanced early warning systems. Nevertheless, dealing with water-related data is the next challenge, owing to nonlinearity, variability, and ambiguous features caused by human influence and unpredictable natural changes. AI models have shown exceptional success and superiority in handling such nonlinear data due to their robustness and problem-solving capabilities

III. MODELING WATER TREATMENT PLANTS AND PROCESSES

Enhancing computer capabilities that are relevant to human understanding, such as knowledge, problem-solving, perception, and cognition, is the primary goal of AI technologies in a system. Many research have used AI models in the past ten years because of their ease of use, quick processing speed, and tolerable mistake without requiring an understanding of physical issues. Numerous uses of AI technology have been tried, including urban water resources and wastewater treatment.

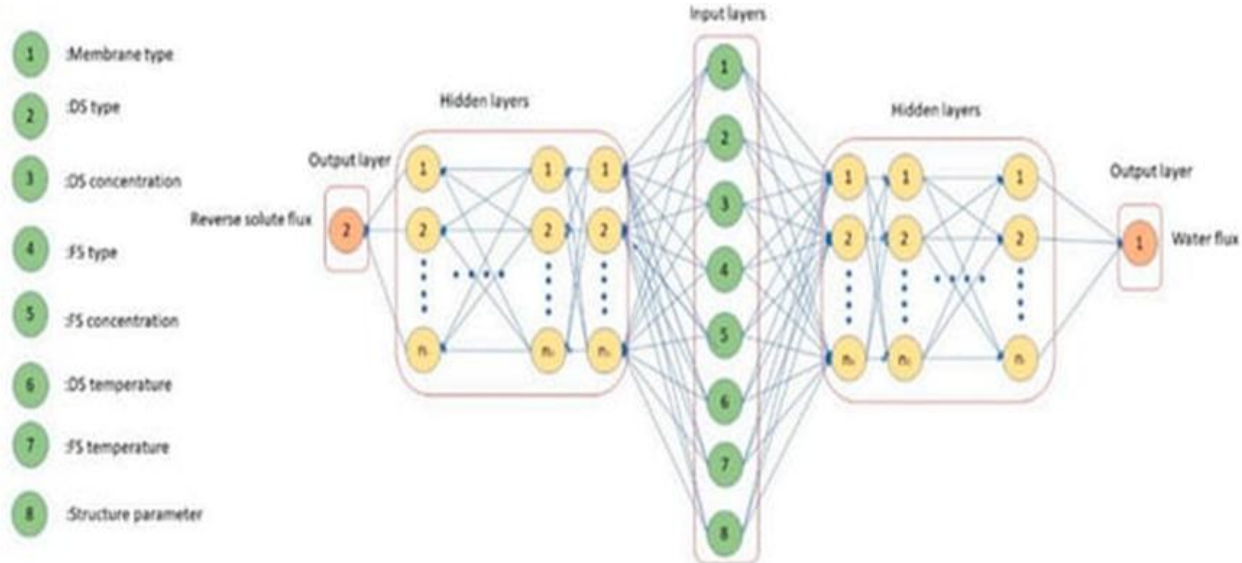


Figure 2. The structure of ANN for predicting the water flux in membranes.

IV. AUTOMATING FILTRATION SYSTEMS

The filtering phase of water purification might be completely transformed by AI-driven automation. Filtration systems may be configured to always run at their best without the need for human intervention by utilizing real-time data and AI models. In order to enable systems to self-adjust the flow rate or start autonomous backwashing procedures, machine learning algorithms, for instance, can forecast the rate of filter blockage based on variables like turbidity and suspended particles.

AI can even reduce chemical waste and increase efficiency in the filtering process by optimizing the usage of chemical coagulants and flocculants. In addition to extending the life of the filters, smart filtration systems lessen the environmental effect of water treatment.

V. DESALINATION AND BRINE MANAGEMENT

The process of desalination, which turns saltwater into drinkable water, uses a lot of energy and generates brine waste, which is bad for the environment. By optimizing the energy needed for the process, artificial intelligence (AI) technologies are assisting desalination facilities in becoming more efficient and reducing their operating costs. AI may also be used to oversee and control brine disposal, making sure that it is carried out in a way that is safe for the environment. Artificial intelligence (AI) algorithms can suggest the best desalination techniques or assist in optimizing reverse osmosis systems for optimum water production with the least amount of energy input by examining trends in energy usage and water salinity.

VI. WATER DISTRIBUTION OPTIMIZATION

AI also is crucial to the optimization of water distribution systems. Real-time supply adjustments by utilities are made possible by machine learning models that forecast water demand across several locations. This enhances the sustainability of water systems, guarantees fair distribution, and lowers water waste. By evaluating pressure data and flow rates, AI can also identify pipeline leaks or inefficiencies, assisting utilities in identifying issues more quickly and minimizing water loss.

VII. AI-DRIVEN DECISION SUPPORT SYSTEMS

Operators and engineers may now make more informed decisions about water treatment because to the growing integration of AI tools into decision support systems. These systems give plant managers useful information by combining sensor data, prediction algorithms, and past performance. AI makes it possible to manage water purification facilities in a more data-driven manner, whether it is by enhancing overall operational efficiency, modifying treatment processes, or optimizing energy consumption.

VIII. OVERVIEW OF THE PROCESS OF AI TOOLS FOR WATER PURIFICATION:

Step 1: Gathering Information
1. Sensor Integration: Use sensors to gather information on temperature, turbidity, pH, and pollutant levels, among other water quality factors.
2. Data Transmission: Send the gathered data for analysis to a central server or cloud-based platform.

Step 2: Analysis of Data
1. Use machine learning (ML) algorithms to examine the gathered data and find trends, patterns, and connections.
2. Anomaly Detection: Look for outliers and abnormalities in the data that could point to problems with the quality of the water.
3. Predictive Modeling: Create predictive models to estimate pollutant levels and water quality metrics.

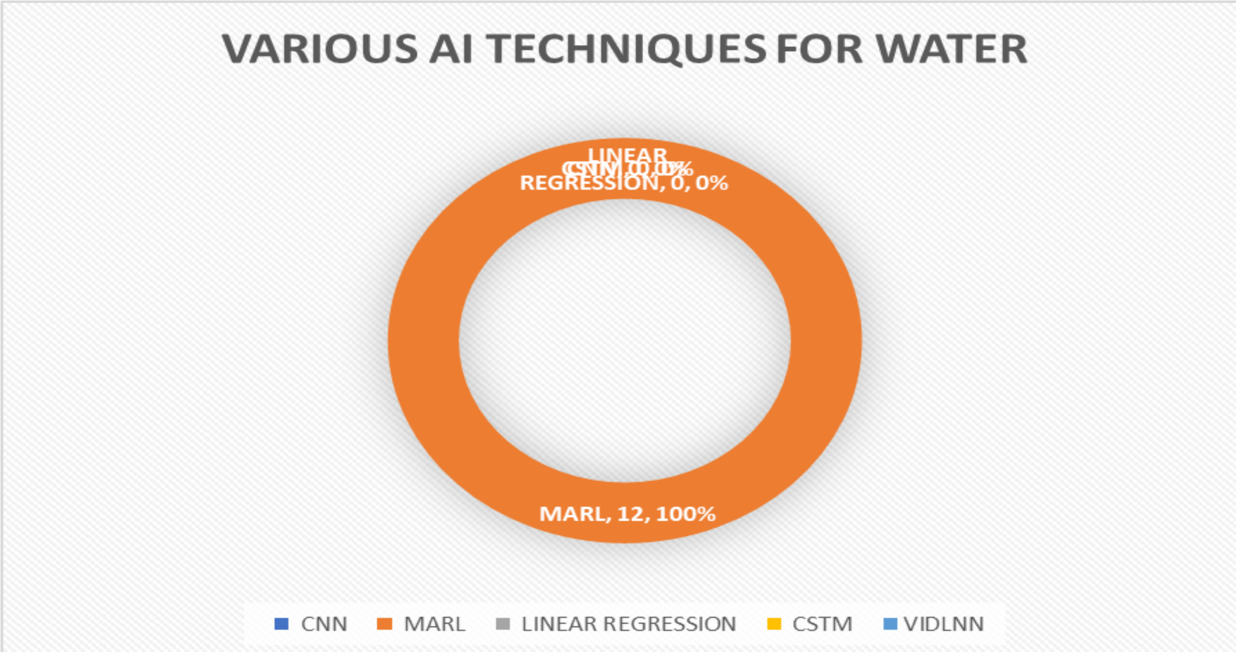
step 3: Monitoring Water Quality
1. Real-Time Monitoring: Use sensors and analytics driven by artificial intelligence to keep an eye on the quality of the water in real time.
2. alarm Systems: Install alarm systems to inform stakeholders and operators of problems or irregularities with the quality of the water.
3. Dashboards and Visualization: To offer insights into data and patterns related to water quality, create dashboards and visualizations.

Step 4: Optimization of the Treatment Process
1. Optimization Algorithms: Using prediction models and real-time data, optimize water treatment procedures by using optimization algorithms.
2. Automated Control Systems: Use automated control systems to make real-time adjustments to treatment procedures.
3. Energy Efficiency: Find options for energy

step 5: Upkeep and Fixing
1. Predictive Maintenance: To anticipate equipment breakdowns and plan maintenance, use machine learning algorithms and predictive models.
2. Automated Reporting: To record maintenance and repair operations, create automated reports.
3. Supply Chain Optimization: To guarantee prompt delivery of supplies and spare parts, optimize supply chain activities.

IX. DIFFICULTIES AND RESTRICTIONS

AI has a lot of promise for purifying water, but there are still a number of obstacles to overcome. To properly train AI models, a significant obstacle is the requirement for vast quantities of high-quality data. The efficacy of AI applications may be constrained by the lack of full, consistent, or accessible water quality data in many areas. Additionally, smaller water utilities may find it difficult to use AI solutions due to the significant training and technological investments needed.



Another issue is the complexity of integrating AI into existing infrastructure. Many water treatment plants rely on legacy systems that may not be compatible with advanced AI tools.

As such, updating these systems or integrating them with AI solutions can be both time-consuming and costly.

X. CURRENT GAP OF KNOWLEDGE AND FUTURE PROSPECTS OF AI TECHNOLOGIES

In a number of water treatment processes, artificial intelligence has clearly outperformed traditional modeling techniques. The successful use of these technologies encourages more study and development of model structures to get around some of the obstacles that prevent them from operating well in the water treatment sector. Among the drawbacks of the most recent AI technology are several operational irregularities in real-world systems.

XI. DISCUSSION

Difficulties with Water Purification

1. Contaminant detection: Recognizing and detecting several types of pollutants, including chemicals, bacteria, and viruses.
2. Optimization of treatment processes: Improving treatment procedures to effectively eliminate impurities.
3. Real-time monitoring: Constantly keeping an eye on the quality of the water.
4. Predictive maintenance: anticipating and averting malfunctions in equipment.

Examples from the Real World

1. IBM's Water Management System: This real-time water quality monitoring and management system makes use of AI and IoT sensors.
2. Xylem's Water Treatment Platform: Predicts water quality and optimizes water treatment procedures using AI and ML.
3. The AI-Powered Water Quality Monitoring program of the Water Research Foundation employs AI and ML to continuously monitor and forecast water quality.

XII. FUTURE DIRECTIONS

1. Integration with IoT sensors: Gathering data on water quality in real time by integrating AI with IoT sensors.
2. Creation of new AI algorithms: Creating new AI algorithms to enhance treatment process optimization and predictive analytics.
3. Growing adoption: AI is being used more and more in water purification across a range of sectors and applications.

CONCLUSION

The non-linearity and intricate process dynamics make it challenging to study and forecast water quality. As a result, a lot of research fields think that using improved AI models to interpret historical data is a viable approach. The effectiveness of treatment and end users' safety when using water can both be enhanced by models and forecasts of water quality metrics. To preserve living things and the environment from contamination, wastewater treatment is crucial. Filtration and adsorption by membranes.

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REFRENCE

[1] Abas, P.E.; Mahlia, T. Techno-Economic and Sensitivity Analysis of Rainwater Harvesting System as Alternative Water Source. *Sustainability* 2019, *11*, 2365.

[2] Filali, H.; Barsan, N.; Souguir, D.; Nedeff, V.; Tomozei, C.; Hachicha, M. Greywater as an Alternative Solution for a Sustainable Management of Water Resources—A Review. *Sustainability* 2022, *14*, 665.

[3] Fane, S.A.; Liu, A.; Falletta, J. Assessing Minimum Water Efficiency Standards for Plumbing Products in Homes and Business. *Water Supply* 2024, *24*, 1164–1175.

[4] Nazemi Rafi, Z.; Kazemi, F.; Tehranifar, A. Public Preferences toward Water-Wise Landscape Design in a Summer Season. *Urban For. Urban Green.* 2020, *48*, 126563.

[5] Eshoul, N.; Almutairi, A.; Lamidi, R.; Alhajeri, H.; Alenezi, A. Energetic, Exergetic, and Economic Analysis of MED-TVC Water Desalination Plant with and without Preheating. *Water* 2018, *10*, 305.

[6] Shahid, M.K.; Mainali, B.; Rout, P.R.; Lim, J.W.; Aslam, M.; Al-Rawajfeh, A.E.; Choi, Y. A Review of Membrane-Based Desalination Systems Powered by Renewable Energy Sources. *Water* 2023, *15*, 534.

[7] Dudziak, M. Retention of Mycoestrogens in Nanofiltration. Impact of Feed Water Chemistry, Membrane Properties and Operating Process Conditions. *Environ. Prot. Eng.* 2012, *38*, 5–17.

[8] Wan, L.; Xiong, L.; Zhang, L.; Lu, W. High Loaded Bioflocculation Membrane Reactor of Novel Structure for Organic Matter Recovery from Sewage: Effect of Temperature on Bioflocculation and Membrane Fouling. *Water* 2020, *12*, 2497.

[9] Miao, S.; Ma, J.; Zhou, X.; Zhang, Y.; Chu, H. A Review of CFD Simulation in Pressure Driven Membrane with Fouling Model and Anti-Fouling Strategy. *Front. Environ. Sci. Eng.* 2024, *18*, 93.

[10] Ina, T.; Idomura, Y.; Imamura, T.; Yamashita, S.; Onodera, N. Iterative Methods with Mixed-Precision Preconditioning for Ill-Conditioned Linear Systems in Multiphase CFD Simulations. In Proceedings of the 2021 12th Workshop on Latest Advances in Scalable Algorithms for Large-Scale Systems (ScalA), St. Louis, MN, USA, 19 November 2021; pp. 1–8.

[11] Chakachaka, V.M.; Tshangana, C.S.; Mamba, B.B.; Muleja, A.A. CFD-Assisted Process Optimization of an Integrated Photocatalytic Membrane System for Water Treatment. *Membranes* 2023, *13*, 827.

[12] Goi, Y.K.; Liang, Y.Y.; Lau, W.J.; Fimbres Weihs, G.A. Analysis of the Effect of Advanced FO Spacer on the Specific Energy Consumption of Hybrid RO Desalination System. *J. Memb. Sci.* 2023, *668*, 121247.

[13] Yagnambhatt, S.; Khanmohammadi, S.; Maisonneuve, J. Demonstration of a Real-Time Maximum Power Point Tracker for Salt Gradient Osmotic Power Systems. *Appl. Energy* 2024, *376*, 124205.

[14] Suleman, M.; Asif, M.; Jamal, S.A. Temperature and Concentration Polarization in Membrane Distillation: A Technical Review. *Desalination Water Treat.* 2021, *229*, 52–68.

[15] Habieeb, A.R.; Kabeel, A.E.; Sultan, G.I.; Abdelsalam, M.M. Advancements in Water Desalination Through Artificial Intelligence: A

Comprehensive Review of AI-Based Methods for Reverse Osmosis Membrane Processes. *Water Conserv. Sci. Eng.* 2023, *8*, 53.

[16] Jittawiriyanukoon, C.; Srisarkun, V. Simulation for Predictive Maintenance Using Weighted Training Algorithms in Machine Learning. *Int. J. Electr. Comput. Eng. (IJECE)* 2022, *12*, 2839.

[17] Assegie, T.A.; Rangarajan, P.K.; Kumar, N.K.; Vigneswari, D. An Empirical Study on Machine Learning Algorithms for Heart Disease Prediction. *IAES Int. J. Artif. Intell. (IJ-AI)* 2022, *11*, 1066.

[18] Negri, V.; Mingotti, A.; Tinarelli, R.; Peretto, L. Uncertainty and Lack of Information Affecting the Training of Machine Learning Algorithms for Fault Prediction of Cable-Joints. In Proceedings of the 2023 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), Kuala Lumpur, Malaysia, 22–25 May 2023; pp. 1–5.

[19] Lasisi, K.H.; Abass, O.K.; Zhang, K.; Ajibade, T.F.; Ajibade, F.O.; Ojediran, J.O.; Okonofua, E.S.; Adewumi, J.R.; Ibikunle, P.D. Recent Advances on Graphyne and Its Family Members as Membrane Materials for Water Purification and Desalination. *Front. Chem.* 2023, *11*, 1125625.

[20] AlSawaftah, N.; Abuwatfa, W.; Darwish, N.; Husseini, G. A Comprehensive Review on Membrane Fouling: Mathematical Modelling, Prediction, Diagnosis, and Mitigation. *Water* 2021, *13*, 1327.

[21] Jawad, J.; Hawari, A.; Zaidi, S. Modeling and Sensitivity Analysis of the Forward Osmosis Process to Predict Membrane Flux Using a Novel Combination of Neural Network and Response Surface Methodology Techniques. *Membranes* 2021, *11*, 70.

[22] Mujtaba, I.M. Modelling and Simulation of Industrial Multistage Flash Desalination Process with Exergetic and Thermodynamic Analysis. A Case Study of Azzour Seawater Desalination Plant. *Chem. Product. Process Model.* 2023, *18*, 73–95.

[23] Jawad, J.; Hawari, A.H.; Zaidi, S. Modeling of Forward Osmosis Process Using Artificial Neural Networks (ANN) to Predict the Permeate Flux. *Desalination* 2020, *484*, 114427.

[24] Attarde, D.; Jain, M.; Gupta, S.K. Modeling of a Forward Osmosis and a Pressure-Retarded Osmosis Spiral Wound Module Using the Spiegler-Kedem Model and Experimental Validation. *Sep. Purif. Technol.* 2016, *164*, 182–197.

[25] Alam, M.d.M.; Tirth, V.; Irshad, K.; Algahtani, A.; Al-Mughanam, T.; Rashid, T.; Azim, R. An Adaptive Power Management Approach for Hybrid PV-Wind Desalination Plant Using Recurrent Neural Networks. *Desalination* 2024, *569*, 117038.

[26] Shah, Z.; Raja, M.A.Z.; Khan, W.A.; Shoaib, M.; Tirth, V.; Algahtani, A.; Irshad, K.; Al-Mughanam, T. Computational Intelligence Paradigm with Levenberg-Marquardt Networks for Dynamics of Reynolds Nanofluid Model for Casson Fluid Flow. *Tribol. Int.* 2024, *191*, 109180.

[27] Fetanat, M.; Keshtiara, M.; Low, Z.-X.; Keyikoglu, R.; Khataee, A.; Orooji, Y.; Chen, V.; Leslie, G.; Razmjou, A. Machine Learning for Advanced Design of Nanocomposite Ultrafiltration Membranes. *Ind. Eng. Chem. Res.* 2021, *60*, 5236–5250.

[28] Rezakazemi, M. CFD Simulation of Seawater Purification Using Direct Contact Membrane Desalination (DCMD) System. *Desalination* 2018, *443*, 323–332.

[29] Alrefaai, M.M.; Othman, M.H.D.; Rava, M.; Tai, Z.S.; Asnaghi, A.; Puteh, M.H.; Jaafar, J.; Rahman, M.A.; Al-Ogaili, M.F.A. A CFD Analysis of the Desalination Performance of Ceramic-Based Hollow Fiber Membranes in Direct Contact Membrane Distillation. *Ceramics* 2024, *7*, 115–136.

[30] Abrofarakh, M.; Moghadam, H.; Abdulrahim, H.K. Investigation of Direct Contact Membrane Distillation (DCMD) Performance Using CFD and Machine Learning Approaches. *Chemosphere* 2024, *357*, 141969.

[31] Bin Abid, M.; Wahab, R.A.; Salam, M.A.; Moujdin, I.A.; Gzara, L. Desalination Technologies, Membrane Distillation, and Electrospinning, an Overview. *Heliyon* 2023, *9*, e12810.

[32] https://www.sciencedirect.com/science/article/pii/S0011916414005487

[33] https://www.sciencedirect.com/science/article/pii/S2214714415000069
[34] https://www.sciencedirect.com/science/article/pii/S2213343721005133
[35] https://www.sciencedirect.com/science/article/pii/S0959652620319144
[36] Safeer, S., Pandey, R.P., Rehman, B., Safdar, T., Ahmad, I., Hasan, S.W. and Ullah, A., 2022. A review of artificial intelligence in water purification and wastewater treatment: Recent advancements. Journal of Water Process Engineering, 49, p.102974.