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Machine learning-driven advances in polymer membrane science: Emerging trends and future directions

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ABSTRACT

Membrane science is gaining importance in the emerging field due to its fewer energy consumption and low maintenance. Many surveys and studies were concentrating on specific membranes for specific applications. Trial-and-error approaches in membrane design result in inefficiencies, including time and material wastage. There is a need for developing a generalized model with minimal parameters and resulting membrane satisfying separation applications. Enhancement of membrane performance is crucial and hence many researchers considered the fabrication and design aspects of membrane parameters as research criteria for different applications. High surface area, ease of maintenance, and low cost make them attractive to different applications including the bio-medical sector, food and beverages, water filtration, gaseous environment, etc. However, membrane design and configuration demand several experiments specific to the applications. Hence it is still considered to be a challenging process thus opening new avenues towards automating the process. This review comprises a summary of state-of-the-art membrane technology and its application in the separation phenomenon providing a machine learning perspective in membrane science and engineering.

1. Introduction

In a world of advancing technologies, membranes are increasingly recognized for their role in addressing essential needs such as clean water, air, and food, particularly in densely populated regions. Managing resources is challenging as they cost high when the needs are greater. Hence there is a need for supplying basic resources such as clean water, fresh air, and healthy food at minimum

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cost. Conventional methods such as absorption, membrane separation, and cryogenic distillation are discussed for separation applications [1]. Because of its small size, gentle working conditions, and special qualities including large membrane area, self-supporting construction, and simplicity of handling, membrane technology is one of the burgeoning disciplines in water treatment [2]. Membrane filtration technology is the most promising technique in the purification process with the help of suitable dead or cross-end filtration methods for the removal of salts or dyes from water [3]. Membranes are the backbone of separation applications, acting as barriers that allow certain materials to pass through depending on the pore size. Recent advancements in membrane technology have revolutionized various separation applications, offering energy-efficient and environmentally friendly processes with significant industrial implications. These advantages allow them to be used as separators in water treatment, food processing, pharmaceuticals, and more [4]. Hollow fiber membranes are thin noodle-like structures prepared by a spinning process with the help of a spinneret device. The polymer solution is passed into the spinneret device using a gear pump, which uses a certain N_2 gas pressure as a driving force during the spinning process. The bore fluid is passed through the center hole, which helps to provide a hollow inside by forming an inner lumen. By varying spinneret dimensions, air gap, and different concentration rates, it is possible to produce hollow fiber membranes with different thicknesses, diameters, etc. [5]. During spinning, a homogenous polymer dope solution is passed through a spinneret. Under pressure, the polymer solution will be allowed to drop into a coagulation bath, where phase separation takes place, which results in the coagulation and stabilizes the membranes [6,7].

Membranes can be polymeric, inorganic, mixed matrix, thin film composite (TFC), and thin film nanocomposite (TFN). Various types of membranes are used for different applications. Some important parameters and conditions can influence the formation and performance of active layers in TFC membranes. The support layer and its interfacial characteristics properties are other parameters, that can control the characteristic properties of the selective layer [8]. Polymeric membranes are produced from organic materials, and fabricated using electrospinning, phase inversion, stretching, and tract etching. Mixed matrix membranes (MMMs) consist of polymers that incorporate inorganic fillers of nanoscale size through various methods. TFC membranes are made of a thin layer of material that has been selectively deposited on a porous support. TFN membranes are produced when nanoparticles are added to TFC membranes during the production process using a one-step immersion precipitation approach [9]. Novel membrane types like TFC membranes, nanocomposite membranes, and graphene-based membranes have shown improved flux, selectivity, and salt rejection, impacting nanofiltration, reverse osmosis, and gas separation processes [10].Key challenges in scaling up of MMMs for industrial applications include preparation of new materials that maintain high separation performance, ensuring consistent quality during large-scale production, addressing complexities during integration of MMMs into existing water treatment techniques [11]. Transitioning from laboratory-scale to large-scale membrane fabrication poses difficulties in nanofiller aggregation, reproducibility, quality control and, ensuring long-term membrane performance. Additionally, the compatibility between the polymer matrix and inorganic fillers can also affect mechanical stability and separation efficiency of the membrane. Addressing these engineering challenges is crucial for the successful industrial application of MMMs and TFN membranes [12].

Membranes are classified into four groups according to the size of their pores and they are microfiltration (MF), ultrafiltration (UF), nanofiltration (NF), and reverse osmosis (RO).MF membranes have pore size (0.1-10μm) and are mainly used for water purification purposes. UF membranes have pore sizes ranging from (0.1-0.01μm) and are applicable for removing dissolved macromolecules like proteins, viruses, and colloids.NF membranes are designed with pore size (0.001-0.1 μm) and can separate multivalent ions and surfactants. RO membranes are considered to have very small pore size(<1nm) and are usually used for desalination purposes [13].

Membrane morphology plays key role in the separation performance of NF and RO systems. The main factors include thickness and pore size. The thickness of the selective layer plays a major role in both permeability and selectivity, a thicker membrane offers stronger resistance to the flow of solute and water by increasing the diffusion pathways, thereby increasing rejection and lowering permeability. In the case of thin selective layer membranes, the diffusion pathways are reduced, further offering less resistance to the flow of water and solutes, thus increasing permeability and reducing rejection rates. Similarly, larger pores offer less resistance to the water transport facilitating, higher permeability and low rejection, whereas a decrease in pore size restricts water transport, thus reducing permeability and improving rejection capability [14]. Hollow fiber membranes usually show an asymmetric structure with finger-like projections on both the outside and inside as well as a sponge-like structure at the middle portion. Except for pristine membranes, we can observe material presence in all membranes as additives [15], UF membranes are available as hollow fiber (HF) membranes, consisting of long, thin fibers with a hollow core at the center. These fibers are typically made from various polymers or ceramics, and offer higher surface area, making them suitable for various applications such as ultrafiltration and nanofiltration [16]. For example, through a tight ultrafiltration process, Syed et.al.,[17] fabricated graphene oxide based @POLY SBMA-co-MBAAm additive incorporated hollow fiber membranes with different compositions and succeeded by removing 99% - RB5, and 74% - RO16 dye from wastewater, Additionally, they proved effective removal of the salt, achieving higher rejection of NaSO4 than NaCl. The non-solvent-induced phase separation (NIPS) method, which employs organic solvents such as n-methyl pyrrolidone (NMP), is the process used to prepare HF. Water is used as a solvent and non-solvent in aqueous phase separation (APS), another alternate method for membrane production. To create a non-solvent coagulation bath during NIPS, the polymer can be dissolved in an organic solvent and forced through a spinneret. Solid porous film is produced by polymers that are insoluble in non-solvents [18]. For an instance, Mithun Kumar et. al.,[19] fabricated hollow fiber membrane for the arsenic removal from waste water, in this study fabrication of blend hollow fiber membranes is processed by nonsolvent induced phase separation method. The PVP and PPSU polymers are in fixed composition and Polydopamine as additive with various composition. Through this work successfully achieved the overall membrane performance and rejection efficacy of HF membranes. They offer high packing density, high mechanical strength, and ease of module assembly, making them favorable for water and air purification processes. Vainrot et. al., [20] works states that preparation of the poly sulfone membranes with use of non-solvent induced phase inversion method, there are three pore formation methods are employed to fabricate psf membrane, those are noniron acid etching, base hydrolysis in binary blends and in base hydrolysis of cross-linked polymers. Characterization conclude and confirm that uniform pore formation achieved hydrolysis of cross-linked polymers and binary blends. These membranes showed greater water flux about 3000 L/m^2h at 10 bar pressure and also achieved monovalent and divalent ions removal from aqueous solution, as results these membranes suitable and strong potential capability towards water treatment process. Hence these fibers can find diverse applications such as water purification, gas separation, and food and beverage industries which will improve resource scarcity required in daily life [21,22].

Additives play an important role in increasing the pure water flux by increasing the porosity and hence hydrophilicity of the membrane. Different class of additives have been widely incorporated into hollow fiber membranes to optimize their structural and surface properties. Hydrophilic functional group of the additive or surface functional groups of the additives introduce polar functional groups on the membrane surface, thus lowering contact angle and improving water permeability. The functional groups of the additives also influence the rate of de-mixing of solvent and non-solvent during phase inversion, further affecting the porosity of the membrane. Carefully tuning the concentration and type of additive, optimized porosity of the membrane can be achieved. The functional groups introduced on the membrane by the additives offer resistance to the attachment of the foulants through electrostatic interaction, thereby inducing antifouling character to the membrane. In Valeen Rashmi Pereira et. al.,[23], did research works showing the impact of amine-functionalized nano SnO_2 and TiO_2 as additives to evaluate the performance and hydrophilic properties of PSF membranes, the flux study, and antifouling properties are effectively improved. these membranes are also used to eliminate the cadmium ions effectively from the aqueous solution. An experimental study conducted by Mansor & Sobran, [24], used titanium dioxide (TiO2) as an additive, and dimethyl formamide (DMF) as a solvent in the preparation of polyvinylidene fluoride (PVDF) HF membrane fabrication. A comparative study was performed by adding cellulose acetate (CA) and cellulose acetate phthalate (CAP) to prepare polyphenylsulfone (PPSU) HF membranes. It was observed that the HF membrane prepared with the addition of 5 wt% of CAP in PPSU was found to have improved arsenic removal from water than the HF membrane prepared with 5 wt% of CA in PPSU. According to a study of structural morphology, it was observed that finger-like projections increase with the increase in hydrophilic additives [25]. Microspheres are utilized as an additive to enhance the performance of manufactured membranes. The demonstrated membranes improved the hydrophilicity, as well as water uptake capacity, also these membranes notably protein rejection, good flux recovery ratio, and higher permeability value. Mainly these membranes promise notable removal percentages of proteins 94.8% of BSA, 68.4% of pepsin, and 86.9% of egg albumin from waste water [26]. Surface characteristics modification such as pore size reduction and pore size distribution happens with the addition of polyethyleneimine (PEI) in the case of dye fractionation of textile wastewater process using NF HF membrane as observed by Han et al., [27]. Banjerdteerakul et al [28] fabricated 3 different membranes with variable outer diameters, inner diameters, and thicknesses. Membranes with high coating time(thickness) resulting more nonselective pathways called wrinkles reducing sieving performance but increasing the separation. Porous graphene oxide (PGO) HF substrate membranes were found to have good separation performance for membranes with small diameters and higher curvature. The hydrophilic nature of hollow fiber membranes is characterized by the contact angle, various functional groups on the surface of membranes, thickness, surface morphology, internal microstructure, topography, elemental composition, bond energies, weight loss, and charge of the membranes are studied by the Fourier Transform Infrared Spectroscopy(FTIR),Transmission Electron Microscope(TEM), Scanning Electron Microscopy(SEM), Energy Dispersive x-ray Spectroscopy(EDX), X-ray Photoelectron Spectroscopy(XPS),Thermogravimetric Analysis (TGA), and Zeta potential respectively, also other experimental studies like water uptake, rejection, fouling, pure water permeability, were carried out during respective filtration process [29].From the past literature, it is understood that the membrane and its morphology rely on various factors such as choice of polymer, solvent, non-solvent, composition of bore liquid, operating conditions, and spinneret dimensions [30].

Many challenges such as fouling, flux reduction, permeability-selectivity trade-off, and the long-time process will direct us to choose machine learning (ML) based techniques. Many research studies/pilot studies conducted using membrane units required long-term monitoring and chances of wastage of materials. Fabrication of membranes for different applications was carried out through a lot of repetition of experiments. The correlation of operating conditions and membrane morphology is also considered a challenge. All these aspects motivate to design of ML models for automating the processes.

ML techniques contribute by autonomously learning from historical data to predict membrane fouling trends, enabling optimization of operating conditions. This enhances decision-making processes, potentially addressing fouling challenges and improving the permeability-selectivity trade-offs in membrane technology [31]. Cao et al.,[32] in their study discussed different ways by which ML techniques can optimize membrane design by predicting properties, providing insights into performance relationships, and guiding the design process, thereby addressing challenges like fouling and permeability-selectivity trade-offs through data-driven approaches.The study by Zahra et al.,[33] shows that the antifouling characteristics of photocatalytic ceramic membranes for the treatment of oily wastewater can be significantly improved by morphology-engineered $BiVO_4$ photocatalysts. The sheet-like $BiVO_4$ outperformed the star-, sheet-, and sphere-like structures, achieving over 99 percent TOC removal, a 2.5-fold increase in flux, and a notable decrease in irreversible fouling. According to these findings, modifying the shape of photocatalysts presents a viable approach to improving membrane-based water purification. Similar study on integration of visible light-driven $BiVO_4$/rGO and $BiVO_4$/g-C_3N_4 photocatalysts onto ultrafiltration membranes significantly enhances antifouling and self-cleaning performance, achieving over 99% TOC removal, doubled permeate flux, and substantial fouling reduction, demonstrating their effectiveness for oily wastewater treatment [34]. Fouling can be efficiently reduced by raising surface charge density and decreasing electrolyte concentration, according to studies on nanofluidic membranes with polyelectrolyte-coated channels. Furthermore, AC fields function better than DC at middle frequencies when it comes to restricting BSA deposition; however, this benefit vanishes at very low or high frequencies [35]. With a focus on viscous dissipation, ionic selectivity, and Joule heating, the effects of DC and sinusoidal AC fields on ion transport in soft conical nanochannels were examined. Under both co-current and counter-current modes, numerical solutions of the Poisson–Nernst–Planck, Navier–Stokes, and energy equations showed that AC fields considerably reduce Joule heating in comparison to DC. These observations highlight how AC-driven operation might enhance heat control and transport effectiveness in lab-on-a-chip and nanofluidic systems [36]. Related studies of polyelectrolyte-modified nanochannels have demonstrated that ion transport is significantly influenced by both electric field type and geometry. Because of their improved electrical double layer overlap, conical channels operate better than cylindrical ones, exhibiting significant ionic current rectification, higher electroosmotic flow, and stronger ion selectivity. Waveform also affects performance; sawtooth or sinusoidal fields improve selectivity, whereas square and DC fields encourage rectification. These revelations show how constructed nanochannels can be used as programmable ion gates for medication delivery, separation, and biosensing [37]. Ion concentration polarization (ICP)-based nanofluidic membranes have demonstrated a great deal of promise for increasing desalination effectiveness. The layout and quantity of arrays have a significant impact on salt removal, as shown by numerical modelling of positively charged cylindrical nanochannel arrays implanted in microchannels. Dual and triple configurations yielded improved efficiency, but moderate performance. The significance of nanochannel architecture in developing next-generation desalination systems is highlighted by these findings [38]. The study by Hoshyargar et al., [39] compares classical electroosmotic behaviour with the theoretical impacts of ionic size effects on diffusion osmotic flow in a charged slit microchannel. While steric effects always prevent electroosmosis, the research shows that they can improve diffusion osmosis, sometimes even reversing the flow direction toward areas of higher concentration or even double the mean velocity. Diffusion-osmotic flows, in contrast to electroosmosis, are susceptible to steric effects even when thin electrical double layers are present. This is especially true at relatively low zeta potentials of a few tens of millivolts. Due in significant part to the considerable modification of the induced electric field by finite ion sizes, these results demonstrate the special sensitivity of diffusion osmosis to steric interactions.

Additionally, selectivity and permeability of membrane play a major role in understanding the role of interfacial forces particularly electrostatic phenomena. The integration of polyelectrolyte bilayers with charged-wall nanochannels has been shown to greatly improve ionic current rectification by amplifying asymmetry in ion transport. This bilayer strategy enhances ion selectivity and produces stronger diode-like behavior than traditional single-layer or bare channels. Such findings lead to promising applications in nanofluidic sensing, energy conversion, and ion gating technologies [40]. Salinity gradients can be effectively converted into electrical energy using ionic nano transistors, and in comparable circumstances, NPN setups outperform PNP devices. Power production is further increased by optimizing soft layer charge density, underscoring the promise of nanofluidic devices for blue energy harvesting [41]. The impact of surface charge-dependent slip lengths on electroosmotic mixing in wavy micromixers is examined by Khatibi et al.,[42]. The work quantitatively solves the Laplace, Poisson–Boltzmann, convection–diffusion, and Navier–Stokes equations under steady-state circumstances using a finite-element method. According to the results, adding surface charge-dependent slip lengths lowers mixing efficiency; in one scenario, mixing efficiency drops from 95.5% to 91.5% with a diffusive Peclet number of 200. In addition, the study analysed fluid rheology and flow behaviour index affected mixing efficiency and flow field modulation, providing information for creating microfluidic systems with improved mixing capabilities. Permeability and selectivity are two competing requirements that frequently limit the performance of porous-membrane-based osmotic energy producers, making their synergistic optimization a contentious topic. In order to overcome this, scientists combined sulfonated polyether sulfone with graphene oxide to create two-dimensional porous membranes with tunable charge densities. Numerical simulations were used to support systematic investigations that looked at the effects of pore size and charge density alterations onion transport and energy conversion pathways. Results show that for effective ion channel design, these parameters must be aligned optimally. This method achieves a nearly 20-fold improvement over pure graphene oxide membranes by improving power output while balancing permeability and selectivity [43]. A predictive model for the conductivity–selectivity trade-off in ion-exchange membranes (IEMs) is presented by Kitto and Kamcev,[44] with the goal of determining an upper bound for energy conversion applications. Their framework measures the effects of changes in ion transport characteristics on conductivity and selectivity by combining ion diffusion coefficients, membrane architecture, and electrostatic interactions. They use this model to find the ideal membrane properties that balance the trade-offs between ion conductivity and selective permeability while optimizing performance. The paper offers a theoretical framework for creating IEMs with increased efficiency in fuel cell and electrodialysis operations. Ionic current rectification and selectivity are greatly improved by applying dense polyelectrolyte brushes on bullet-shaped nanochannels. This is because of ion partitioning effects between the electrolyte and polyelectrolyte layer. At moderate salt concentrations, numerical simulations demonstrate that taking these interactions into account can raise the rectification factor from 3.35 to 4.88, underscoring their significance in the design of effective soft nanochannels [45]. With an emphasis on their possible uses in nanoelectronics, work by Alinezhad et al.,[46] examines the ionic transfer behaviour of bipolar nanochannels modeled after PNP nano transistors. The study uses numerical simulations to solve the Navier-Stokes and Poisson-Nernst-Planck equations, investigating how ion transport is impacted by applied voltages and electrolyte concentrations. Results show that the ionic current fluctuates with concentration ratios and voltage polarity, with a significant rise in current noted under some circumstances. These discoveries offer promise for improvements in nanoscale electronic devices by advancing our knowledge of the ion transport pathways in nanochannels.

Some of the research gaps that are identified from the literature review on membrane technology are as follows.

a. Need for development of dynamic models: Most machine learning models for membrane separation are static, assuming constant conditions. There is a gap in developing dynamic models that can adapt to changing operational parameters, such as flow rates, feed compositions, and fouling over time.
b. Real-time monitoring and control: Integrating machine learning models with real-time monitoring and control systems for hollow fiber membrane processes is an ongoing challenge.

c. Uncertainty Quantification: There is a gap in developing methods to quantify and propagate uncertainty in machine learning predictions is crucial for decision-making.
d. Scalability and generalization: Ensuring that machine learning models generalize well across different membrane materials, geometries, and operating conditions is a persistent challenge.
e. Interdisciplinary collaboration: Promoting collaboration between experts in machine learning, materials science, chemical engineering, and biotechnology is crucial to addressing research gaps and fostering innovation in the modeling of hollow fiber membranes for protein separation.

In the developing era of technological aspects, machine learning programming has created a great impact on automating various aspects in different fields. The application of machine learning techniques can enhance the ability to predict and optimize the performance of HF membrane systems. By analyzing various design parameters such as membrane material, pore size, surface chemistry, and operating conditions, ML algorithms can identify complex relationships and patterns that influence separation efficiency.
This approach will enable the development of more accurate models for predicting membrane performance, ultimately leading to the design of highly efficient and cost-effective protein separation processes. Research articles focused on intelligent and traditional models for the removal of suspended particles infer the utilization of different models leading to optimized results [18].
The following section contains details of the study conducted on hollow fiber membranes for separation applications. The current needs and challenges in membrane technology in separation processes motivated to frame the objectives of this review are as follows.

1. To highlight the various types of membranes and their applications in separation processes.
2. To brief about current advancements in membrane technology.
3. To understand the role of ML in membrane technology.
4. To discuss the advantages of ML in membrane technology and the scope of membrane technology in the future.

2. Methodology

This review is conducted in a systematic way approaching existing literature on a particular topic. This study involves defining a problem, reviewing articles, that meet inclusion/exclusion criteria, and assessing relevant data [47]. The study aims to get insights related to “membrane for separation”, and “membrane technology latest trend and future scope” and to explore the applications of membrane technology in various fields. Review is carried out between the period March 2023 and September 2024 to explore the technological advancement and future scope of membrane technology and its applications.
Here preferred reporting items for systematic reviews and meta-analyses (PRISMA) tool is used to illustrate the transparency of the literature survey.

2.1. Study selection

The literature review was performed using iterative and systematic searches on online databases including Scopus, IEEE Xplore digital library, ScienceDirect, PubMed, and ACM. The search strings considered were ((“Membrane Technology”) OR (“Membrane Science”) AND (“for separation”) OR (“for purification”) AND (“Separation Applications”)). The inclusion and exclusion criteria are listed in Table 1.

Table 1. Inclusion and exclusion criteria

Sl. No	Inclusion criteria	Exclusion criteria
1.	Design or fabrication of hollow fiber membrane	Studies reported in languages other than English
2.	Simulation study of modeling membrane	Design or fabrication of other fiber modules
3.	Review articles exploring the state-of-art-of membrane technology	Articles/journals before the year 2015
4.	Membrane technology for different applications	Patent, thesis for membrane study

2.2. Need for study and challenges

The motive behind the study is to understand the current trend of membrane, its applications, specifically on separation processes. Since the technology is developing infinitely there is a need to grab available intelligent techniques using which process can be monitored easier and faster. Membranes being highlighted due to their lightweight, low cost, environmental-friendly characteristics, need for applying optimization techniques towards improvement of results and reduction of fouling are becoming research interests.

Combining available ML techniques for the present challenges lead to fruitful results.

During the review period, articles accessed through the internet are listed in MS Word and information is extracted.

- Publication details (author name, year, country) were tabulated.
- Dataset information (type of study, material /data) noted.
- Methodology (Name of algorithm, Simulation details) noted.
- Insights from the articles noted.

A brief description of the bibliometric analysis of accessed articles performed is shown in Figure 1. It can be inferred that membrane science, and its applications have been increasingly gaining importance from 2010 onwards.

In the Figure 2, geographical context-based analysis has been shown. Most of the research was carried out by China followed by India, and Iran. Some of the research works were carried out in collaboration with different universities and territories.

As the population increases year by year, sustainability and the need for resources are becoming a challenge for survival leading to more and more inventions in countries such as China and India.

Based on the search patterns, materials were accessed using the Scopus database containing different categories such as research articles, review articles and so on. There were 46% research articles, 23% review articles,19% book chapters,10% conference papers, and 2% books accessed as shown in Figure 3.

After restricting the article's title, abstract, and author's keywords, a total of 238 articles were found.

There were no domain restrictions on the search discipline. Subsequently, 138 articles were selected under inclusion and exclusion criteria. Based on the relevance duplicated articles were removed.

A screening and consideration process was used for the selected articles' reference lists. Finally, a total of 44 articles were considered for the review.

The systematic literature will not be complete without a PRISMA diagram. It is the systematic way of representing the literature work in terms of a flow diagram [48].

Figure 4 depicts the schematic depiction of the systematic review procedure.

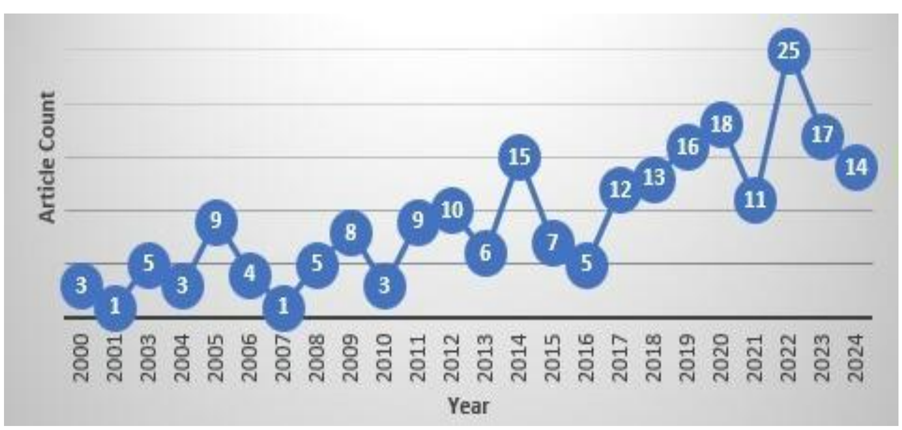

Fig. 1. Year-based analysis considering the starting year from 2000.

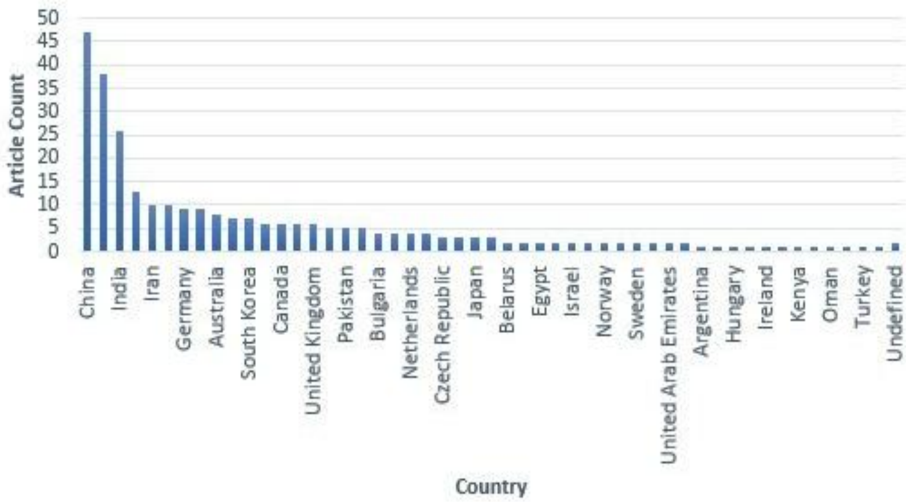

Fig. 2. Geographical context-based analysis

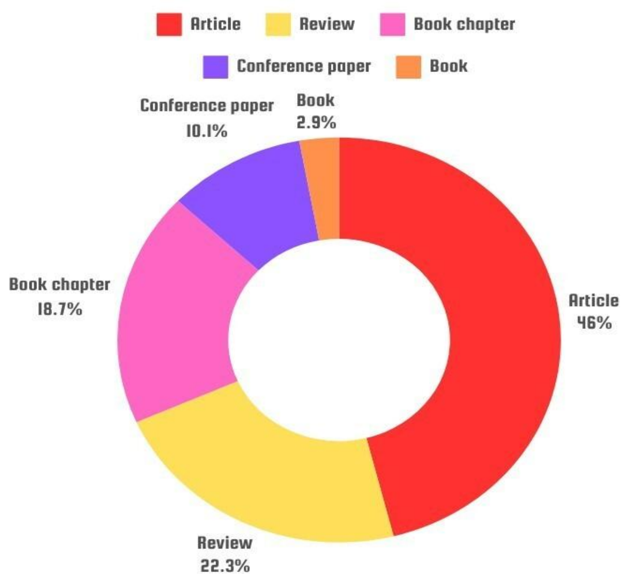

Fig. 3. Document type analysis

3. Different types of membranes and their applications in the separation process

Membranes are versatile and essential in various industries due to their ability to selectively separate substances. There are many ways in which membranes can be categorized. Based on the filtration process they are classified into MF, UF, NF, and RO.

Table 2 gives details of each filtration process. Membrane module layouts may be divided into four categories such as spiral wound, flat-sheet, HF, and tubular membrane modules.

Tubular modules consist of cylindrical tubes made up of polymers, ceramics, or metals and diameters ranging from millimetres to centimetres with membranes placed at the inner surface of the tube. Tubular membranes often require a support layer to provide mechanical strength. This layer is typically a porous substrate that supports the thin selective membrane. A HF membrane module consists of numerous thin, flexible tubes with a porous or semi-permeable membrane wall that facilitates selective separation. These fibers are bundled together and encased within a cylindrical housing, forming a module. The core element of these modules is the HF, which is a thin, flexible tube with a diameter typically ranging from 0.1 to 1 mm.

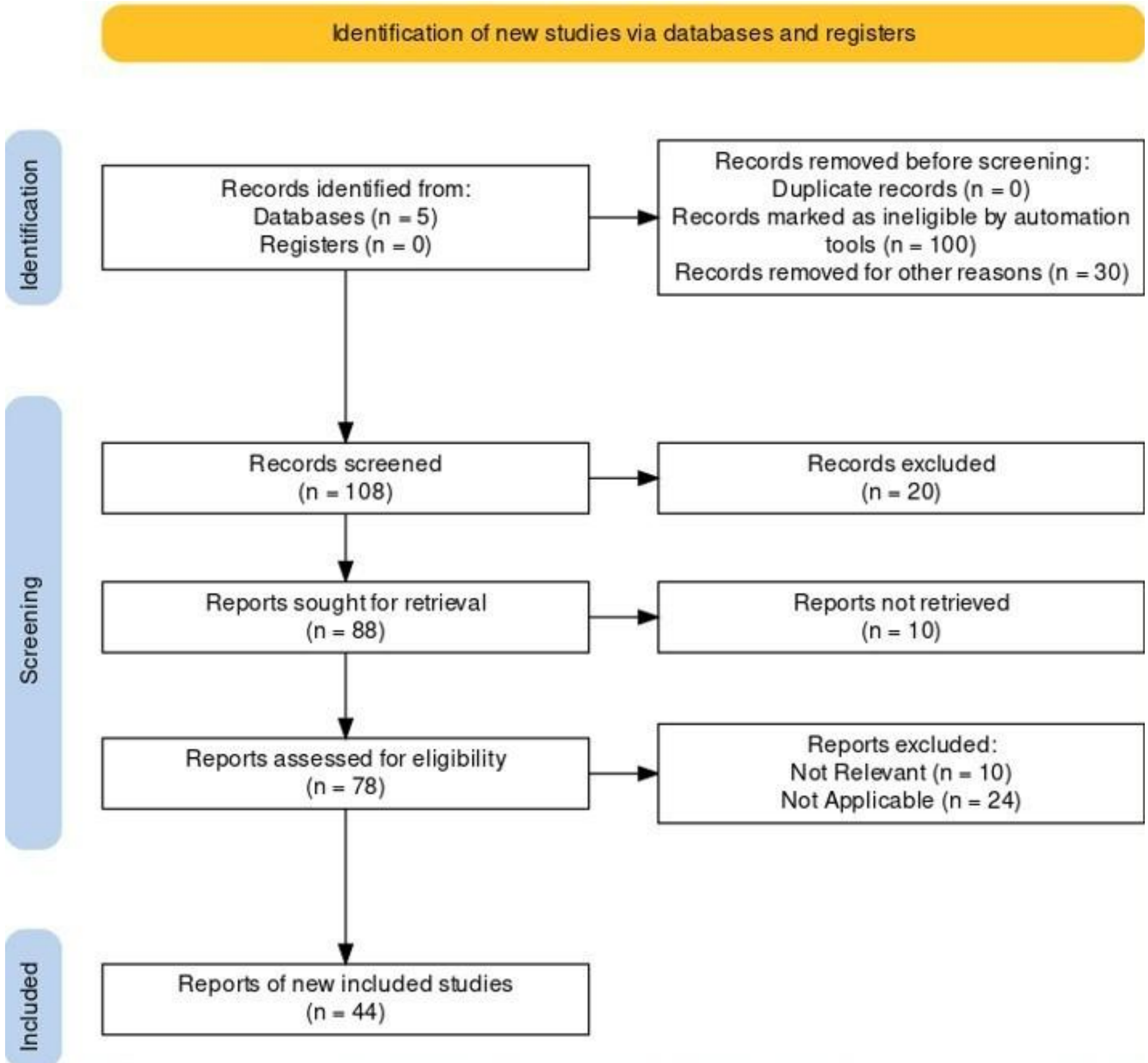

Fig. 4. Literature review process

The design leverages the high surface area provided by the numerous small-diameter fibers to achieve efficient separation in a compact form. The permeate carrier, feed spacer, and membrane sheets are coiled around the center collecting tube in the spiral design. The porous substance is sandwiched between the membrane sheets to allow the feed solution to pass through them. It helps to maintain separation between the layers and promotes turbulent flow to reduce fouling. A fabric or mesh material that collects the permeate and directs it to the central collection tube.

A perforated tube is located at the center of the module, where the permeate is collected and transported out of the module.

Flat sheet membrane module configuration consists of flat membrane sheets typically made of polymers such as PES, PVDF, or CA. The flat sheets are supported by rigid or semi-rigid plates, which provide structural integrity and support the membranes against the pressure of the feed flow. Spacers or gaskets are used to separate the flat sheets and create flow channels for the feed solution.

These spacers ensure even distribution of the feed across the membrane surface. The flat sheets, along with their support plates and spacers, are typically arranged in a stack within a frame. Multiple cassettes can be housed within a larger pressure vessel or module housing. Channels are designed to collect the permeate and direct it to the permeate outlet, while the concentrated retentate exits through a separate outlet.

There are two types, based on configuration namely dead-end and crossflow. When arranged in a dead-end arrangement, the permeate is collected on one side of the membrane and the feed solution is routed perpendicular to its surface. This is suitable for applications with low particle concentrations or where high retention of particles is desired.

They can be commonly used in laboratory-scale filtration, small-scale water purification, and certain types of sterile filtration. Crossflow configuration is often highly preferred, where the feed solution flows tangentially across the membrane surface. A portion of the feed passes through the membrane as permeate, while the rest continues to flow parallel to the membrane, carrying away retained particles. These are suggested for applications with high particle concentrations and are widely used in industrial processes, including wastewater treatment, desalination, and the dairy industry for milk concentration [49].

Membrane categorization can be visually represented as shown in Figure 5.

3.1. Membrane applications in water purification

Membrane-based water purification process is gaining importance because of fewer energy consumption and environmental friendliness compared to conventional purification techniques like chlorination, and sedimentation. Many water treatments suffer problems like membrane fouling. Fouling is a phenomenon of attachment of organic matter above the membrane surface.

A study on cleaning agents and cleaning protocols was done by Zhao et al., [50]. Contaminants can be blocked by a semipermeable barrier according to their pore size, charge, and chemical makeup. The process of water purification is categorized into MF, UF, NF, and RO based on their pore size.

Multiple wastewater resources and treatments can be found. One such study investigates ammonia capture from various wastewater streams like human urine [51].

Ozonation is another type of water treatment studied by Wang et al., [52], in which they used ML models for the simulation of ozonation. Study on the influence of dominant salts on NF study for micropollutants removal explained by Rutten, S. B., et al., [53].

A study of mixed matrix HF polymeric membranes preparation with PES/PVDF, investigation on different polymer ratios and their effects on performance was carried out by da Silva Biron et al., [54].

It was noticed that low PES/PVDF ratios improve membrane hydrophilicity, thereby enhancing performance. Some of the membrane-based applications for water purification are listed in Table 3.

Table 2. Details of the filtration process

Process	**Pore size**	**Driving force**	**Particles removed**	**Applications**
MF	0.1-10μm	Pressure, 1-2 bar	Protozoa, Algae, Bacteria	Water treatment
UF	0.01-0.1μm	Pressure, 2-5 bar	Macromolecules, micro molecules, germs, viruses	Food processing, Pharmaceuticals
NF	<2nm	Pressure, 5-15 bar	Hardness, monovalent ions, divalent ions, micro molecules	Diary and medicinal applications
RO	<1nm	Pressure, 15-100 bar	-	De-saline applications

Table 3. Membrane applications in water purification

Ref	Methods	Results	Type of membrane
[50]	Morphological analysis: SEM	FO membrane reduced PPW volume by 50% at 15.6 $Lm^{-2}h^{-1}$	FO HF membrane
[51]	Experimental and calculation	Ammonia mass transfer coefficients ranged from $1.95x10^{-6}$ to $2.28x10^{-6}$ m/s	HFMC
[52]	CFD and ML for ozonation process ML: SVR, DTR, OMP Bat algorithm for optimization	SVR model outperformed others with MSE 0.003, R^2 0.998, MAE 0.046	HFMC
[53]	Analytical methods	dnF40 MP removal>85% dnF80	HF NF membrane
[54]	Morphological analysis: SEM Hydrophilicity: sessile drop technique	Contact angle 78.4 for PES 92.3 for PVDF	Mixed matrix HF

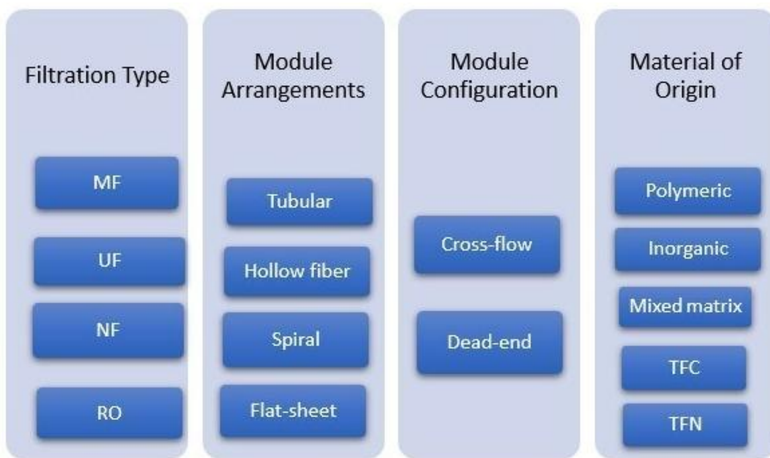

Fig. 5. Membrane classification

3.2. Membrane applications in food and beverages

Membrane-based food processing involves using semi-permeable membranes to separate and purify components in liquid food and beverages. In the dairy industry membrane separates bacteria, removes excess fat content, and thus improves nutritional value and improves quality. Reducing waste contents in fish and meat processing prevents the unnecessary use of chemicals. Using the filtration process it is possible to reduce operational costs and improve process efficiency [55].

The application of UF for the separation of lactose, vitamins, and minerals through whey purification explained by Surgey et al., [56]. The use of machine learning in predicting permeate flux is well explained by Poudineh et al., [57]. Here parameters such as membrane material, pore size, pressure, flow rate, and processing time are considered for finding permeate flux. An Intelligent system by Nejad et al., [58] is used for licorice concentration prediction in membrane processes. The adaptive neuro-fuzzy inference system (ANFIS) model was found most accurate and reliable among the backpropagation neural network (BPNN), radial basis function (RBF), and fuzzy inference system (FIS). Research analysis by Vatanpour et al.,[59] highlighted the dependency of operating pressure on permeability and selectivity by keeping some fixed parameters. Table 4 summarizes membrane-based food processing applications

3.3. Membrane applications in the biomedical sector

There are a lot of biomedical applications that also make use of membranes due to their property of selectively separating and filtering biomolecules leading to their use in tissue engineering, dialysis, tissue engineering, and so on [60,61].

The medical industry has benefited greatly from the vast array of uses for membranes. Toxic clearing using hemodialysis needs a miniaturized membrane to be placed for dialysis. An et al., [62] prepared PVDF/ PVDF-g-PACMO blend HF membrane was able to provide promising results in dialysis application. Similarly, Miller et al., [63] developed sheet membranes that could clear toxins at a rate sufficient for animal dialysis. The unavailability of transplant organs will lead to serious issues in needy patients. Membranes can serve as temporary replacements for artificial organs, functioning until a donor is found (Alshammari et al.,[64]).

Membranes play a significant role by providing biocompatibility, facilitating miniaturization, and enabling metabolic functions. Artificial kidneys can be replaced by a hollow-fibered dialyzer created by Tang et al. [65], which offers the advantages of reduced fluid resistance and more surface area. Adsorption property of the membrane used for low-density lipoprotein (LDL) removal application using solution casting technique illustrated by Fang et al., [66]. Membranes with molecular weight cut-off (MWCO) $1.1X10^6$-$1.2x10^6$ Da showed the best performance. Table 5 summarizes applications in biomedical sector.

Table 4. Membrane applications in food processing and beverages

Ref	Methods	Results	Type of membrane
[56]	UF experimental method	Significant increase in permeability for pressure 0.44-0.48MPa Selectivity decreased 95-96%	UF membrane
[57]	ML methods curve fitting, FIS, ANN, and ANFIS are used for modeling permeate flux.	MSE of ANN 0.0495 MSE of ANN 0.0145 MSE of ANFIS 0.0045	-
[58]	BPNN RBF FIS ANFIS	R^2 0.932-0.997 MSE 0.01-1.7%	RO &NF membranes in a spiral wound configuration
[59]	Membrane preparation: TIPS	Blue indigo dye rejection <99%	Polyethylene UF membrane

Table 5. Membrane applications in the biomedical sector

Ref	Methods	Results	Type of membrane
[62]	HF membrane preparation: NIPS Structure & Performance: XPS	Water flow: 200 L m^{-2} h^{-1} 90% of BSA rejection Rate of urea clearance: 80% Lysozyme clearance rate: 62%	PVDF HF membrane
[63]	Benchtop dialysis studies	For dialysis over four hours Starting urea concentration = 61.1 mg/dL Ending urea concentration = 25.3 mg/dL) average URR was 58.7%	Silicon nitride membrane
[64]	HF preparation: Spinning	Oxygen transfer coefficients: 35% (mg/mL)	HF membrane
[65]	Geometric construction	Healthy human: 500 Daltons solute diffusion Middle: 500–15 k Daltons solute diffusion	HF membrane
[66]	ATR Spectroscopy XPS: Chemical composition characterization	The water contact angle for three membranes (PSF):89.7 ± 3.4◦ SPSF:76.4 ± 3.2◦ SPSF/GLU: 71.2 ± 1.9◦	PSF SPSF SPSF/Dextran

3.4. Membrane applications in textile industries

The difficulties in effectively treating wastewater from textile production are greatly mitigated by membrane technology.

Diverse categories of membranes, including NF membranes, TFC membranes, and polyurethane membranes, have been investigated for their utilization within the textile sector. With the use of these membranes, complex contaminants like dyes, salts, and suspended particles may be successfully removed from textile effluent, improving water quality and minimizing negative environmental effects. The integration of nanoparticles such as graphene oxide (GO) and titanium dioxide (TiO_2) into membranes significantly enhances their performance for applications like dye separation and salt rejection. These nanoparticles improve membrane properties by increasing hydrophilicity, reducing fouling,key and enhancing mechanical and thermal stability. This results in higher water permeability and better separation efficiency, making them highly effective for wastewater treatment applications.[67]

By adding nanomaterials like graphene oxide and carbon nanotubes to polymeric membranes, problems like fouling are addressed and the membranes become more hydrophilic, reject more water, and have higher rejection rates. In essence, the application of membranes in the textile industry holds significant importance for promoting sustainable water management practices and safeguarding the environment [68].

The nanocomposite HF membrane was fabricated using a dry-wet spin technique with different additive dosages by Hebbar et al., [69]. With the addition of 2 wt. % poly m – aminophenol (PHNT) concentration, membranes improved in terms of hydrophilicity, surface energy, and porosity. A PVDF HF membrane prepared by Liu et al., [70] for separation of dye, exhibited high flux and long-term stability. The effect of pH, dye, and salt concentrations was studied, and the membrane showed 99.99% rejection and 12% rejection for salts. An adsorption experiment followed by UV-VIS spectroscopy for two types of membranes. The first type consisted of cellulose-based, and the second type was commercial using anthraquinone and azo dye separately. From experimental results, both CMC/CNF-based membranes achieved 100% dye removal efficiency, while BC and BCox adsorbed only 24.3% and 23.6% of the anthraquinone dye, respectively. For azo dye, adsorption efficiency was 7–9% on CMC/CNF-based membranes, compared with 5.57% on BC and 7.33% on BCox membranes Maleš et al., [71]. A research work focused on functionalizing membranes to remove textile dyes was done by Cockerham et al., [72]. Here, Polycarbonate membranes functionalized with azo dye remove textile dyes effectively. Ahmad et al., [73] developed graphene based PVDF membranes that showed high rejection performance.

This enhanced performance of membranes is related to hydrophilicity. Zulfiani et al., [74] utilized high-density polyethylene (HDPE) plastic waste as a membrane for dye removal. They fabricated HDPE with different percentages of plastic waste, and 15% membrane showed the best performance for rejection. Some of the membrane applications have been discussed in Table 6.

3.5. Membrane applications in gaseous medium

Membrane-based gas separation systems are of paramount importance in a wide array of industries for the production, segregation, and refinement of gases. These systems use a variety of membrane materials, including polymeric and inorganic membranes, to enable efficient gas separation processes. The advancement of membrane engineering improves the integration of unit operations in composite membrane systems, amalgamating different membrane processes in industrial settings. Moreover, membrane gas absorption technology provides a versatile and effective method for eliminating diverse compounds from gas streams, rendering it suitable for compliance with rigorous environmental standards and for retrofits in different industries. In essence, the continual progress and application of membrane technologies are indispensable for optimizing gas separation processes and meeting the evolving requirements of a variety of industrial sectors [75]. Membrane applications for gaseous medium are considered in Table 7. Research by Bernardo P et al.,[76] examined the parameters of temperature, flow rates ratio, air gap, spinneret type (double or triple), spinneret dimensions, dope polymer composition and concentration, and bore fluid composition and concentration while spinning. It was found to have high gas permeation need to use double spinneret, and low air gap distance.

Table 6. Membrane applications in textile industries

Ref	Method	Results	Type of membrane
[69]	Membrane preparation: dry-wet spin technique. Chemical modification: FTIR, TEM, and EDX analysis.	Water flux 104.9Lm^{-2}h^{-1} flux recovery 90.3% removal efficiency 97% and 94% dye for Reactive Red 102 Reactive Black 5 respectively.	Hybrid nanocomposite membranes
[70]	Spinning Morphological characterization: SEM	HFM 99.9% rejection of dyes, pure water flux 13.51Lm^{-2} h^{-1}HFM showed low rejection for NaCl (<10%), high rejection for dye (99.99%)	PVDF HF membrane
[71]	Roughness characterization: CFM Morphological characterization: SEM	Contact angle geometry 0° to 34.5°.	Cellulose Based membranes Commercial type
[72]	Characterization: SEM Rejection and flow rate: spectrometer	Rejection efficiency 96.4%	Polycarbonate membranes
[73]	Detecting chemical compound: FTIS Morphological characterization: SEM	Membranes eliminated 96.6% MB and 88.5% MO. water flux around 170.2 (J/L. h^{-1}.m^{-2}) and 98.2% BSA rejection.	Graphene-oxide-based PVDF membrane
[74]	Membrane preparation: TIPS Membrane characterization: SEM FTIS, contact angle measurements	Tensile strength: 0.3435 MPa. Clearance rates for MO and MB were 2.71 Lm^{-2} h^{-1}, (99.72%) and 4.93Lm^{-2}h^{-1}, (89.8%), respectively.	HDPE Membrane

Table 7. Membrane applications for gaseous medium

Ref	Method	Results	Type of membrane
[76]	HF preparation: dry jet/wet phase inversion Morphological analysis: SEM	CO_2 permeance:13.3 GPU to 50GPU	HF membrane
[77]	Computational fluid dynamics: traverse flow Numerical model: to calculate local Sherwood number on membrane surface	Numerical and experimental data differences: Re 0.8: max 8.3%, mean 2.6% Re 1.3:max 12.7%, mean 1.9%, Re 2.4: mean 6.1%, max 11.2%	Micro structured HF membrane
[78]	Scanning Probe Microscopy: Thickness of coating XPS analysis: polymer composition	CO_2 gas permeance dropped 35% N_2 gas permeance dropped by 14% O2 gas penetration decreased by 22%.	HF membrane
[79]	Experimental analysis	Degassing efficiency in CH_4: 95.7%. Degassing efficiency for CO_2 :76.2%	HFMC
[80]	HF preparation: dry/wet spinning Membrane morphology: SEM	O_2 permeance:30.8 GPU, O_2/N_2 selectivity:4.7 thickness: 5–10 μm.	HF membrane

Research on microstructure HF membranes for oxygenator performance enhancement was conducted by Ecker et al., [77].

They observed that improving the region in question by modifying the membrane shell surfaces does not always translate into improved oxygenator performance. An explanation centered on the use of plasma polymerization to alter membrane pore size, as demonstrated by Sharma et al., [78].

Studies on the aging properties of silicone and fluorosilicone in different settings have shown that

the aging process does not affect all applications for membranes coated with plasma polymer equally. Applying an HF membrane for recovering dissolved gas was experimented with an anaerobic membrane bioreactor unit by Sohaib et al., [79].
The degassing efficiency was found to be 95.7% for CH_4 and 76.2% for CO_2, at a gas-to-liquid ratio of 1. In a matrimid-based thin film composite HF membranes study performed by González-Revuelta D et al., [80], it was found that the permeance and selectivity can be increased to improve the gas separation application by having multilayer HF membranes made of matrimid and PDMS having PVDF support. Coating of polydimethylsiloxane (PDMS) helps in thin dense layer structure with a porous nature by PVDF support.

4. Current advances in membrane technology: Role of machine learning in membrane design

ML technique is a powerful technique where machines can predict the outcome based on the training [81]. ML is gaining importance in the advancement of membrane science as it significantly contributes to the design, fabrication, and performance prediction of membranes [82].
Additionally, ML has been employed to establish correlations between membrane performance indices, properties, and fabrication conditions, guiding the design of UF membranes with antifouling potential. Furthermore, ML implementations have enabled the discovery of innovative polymers with ideal gas permeabilities, offer insights into material design, performance enhancement, and the discovery of novel membrane materials with superior properties. In essence, the integration of ML in the field of membrane science not only provides valuable insights into material design processes and performance improvement strategies but also aids in the identification of novel membrane materials that exhibit superior properties compared to traditional methods [83-85].
ML is playing a vital role in advancing the field of polymer HF membrane science and these innovative applications are revolutionizing the development, optimization, and performance prediction of membranes for various industrial, domestic, and scientific purposes. ML algorithms can be utilized for various applications [86-88]. However, these algorithms help mainly in four aspects of the design of HF membranes as shown in Figure 6. In the present review, an overview of the state-of-the-art methods that utilized ML for these applications is considered.
In order to create a robust machine learning model, we must guarantee that the model can be trained using the greatest amount of pertinent data and that it can forecast performance metrics from a membrane perspective. Wang et al., [89] in their work focused on different water/organic mixes and operating conditions utilizing an experimental dataset that included 681 samples, including 16 polymers and 6 organic solvents. Glaß et al. [90] used datasets that included zeta potential and pure water permeability, two performance metrics of modified membranes. A distinct set of datasets is used by various applications; these datasets are necessary to create precise machine learning models for membrane design and optimization. The development of a reliable and accurate model is equally the responsibility of each dataset.

Fig. 6. Role of ML in material science

4.1. Material design and selection

ML algorithms can assist in predicting the properties of polymer materials, aiding researchers in selecting the most suitable polymers for HF membrane fabrication based on desired characteristics such as permeability, selectivity, and mechanical strength. As evidence of the utility of ML algorithms in material design, to evaluate the ideal operating conditions of an HF membrane for CO_2 separation, research by Jasim et al., [91] compared the results of the mathematical model with the computer fluid dynamics (CFD) simulation tool. Comparable results were obtained from the experimentations. Another study by Kim et al., [92] proposed the separation of CO_2 from atmospheric air using a HF membrane in a 'greenhouse'. The air quality data was analyzed using the statistical package for the social sciences (IBM, SPSS Statistics 22.0.0.0) tool. However, such systems have certain limitations such as maintenance and cost. In such a scenario, ML can be utilized to replace computational tools.

Membranes can be of organic and inorganic types. Most of the membranes used in the separation process are organic membranes. Large-scale production of inorganic membranes will cost high. Most organic membranes are made up of polymeric materials. The most widely used organic membrane materials available today are cellulose acetate (CA) and cellulose nitrates, polyether sulfone (PES), polysulfone (PSU), polyacrylonitrile (PAN), polypropylene (PP), polyvinylidene fluoride (PVDF), polyvinyl alcohol (PVA), polytetrafluoroethylene (PTFE), and polyimide (PI). PSU and PES are among the most used polymers for the UF process, whereas PP and PVDF are the most frequently used materials for MF applications. A computational study on nanoporous materials by Yang et al,[90] helped researchers utilize unexplored structural libraries as one of the novel metallic organic frameworks (MOF) designed for the application of CO_2 capture. By using the available datasets such as PolyInfo and the MSA database, they explored new polymers that are very useful in polymer science. With the help of ML models, using prior knowledge helped to find unexplored polymers for the membrane community.

Study of membrane process characterizing several physiochemical and biological interactions which need to be monitored separately. One such study Galinha & Crespo, [93] infers non-mechanistic modeling with the perspective of increasing knowledge and closely monitoring the membrane process. Bestwick et al., [94] concluded certain membrane applications like gas separation need membranes to be constructed with robust and high mechanical strength polymers to reduce the risk factor for usage.

Integration of ML algorithms also lead to more polymer chemistry inventions by predicting permeabilities using the knowledge of monomer structures useful for separation applications. Barnett et al., [95], applied ML algorithms for designing varieties of polymers required for gas separation. They used a literature-based database for six gases by choosing a minimum of 500 datasets for each gas. Polymer characteristics depend on its structure and properties. Tao et al., [96] studied glass transition temperature prediction using different ML models. During that study, a variety of structure representations and feature representations for all possible monomers were analyzed with the help of feature engineering. In predicting transition temperature, RF was found to be the best ML algorithm and 2D convolution neural network (CNN) was the worst algorithm based on the performance matrix. The potential use of the ML algorithm for designing UF membranes based on performance indices and fabrication conditions was demonstrated by Gao et al., [97]. In a computational fluid simulation study conducted to analyze the influence of membrane properties and operating conditions on performance, it was noticed that pore size has a lower influence when compared to membrane thickness and porosity Alwatban et al., [98].

4.2. Membrane performance prediction

ML models can simulate the behavior of polymer HF membranes under different operating conditions, helping researchers predict permeation rates, separation efficiencies, and fouling tendencies before actual implementation. Trial-and-error methodology has persisted in the field of determining the relationship between membrane performance and manufacturing parameters. Research by Gao et al.,[97], infers loading of additives is a crucial manufacturing parameter for predicting membrane performance indices, and operating circumstances have a significant impact on membrane performance. They correlated membrane fabrication conditions with membrane performance determining membrane properties using ML algorithms. The important aspect of their study is transmembrane pressure negatively correlated with water permeation. It is also found that the molecular weight of contaminants positively correlated with removal efficiency and mean pore radius is negatively correlated with removal efficiency. HF membranes are extensively used as vehicular humidifiers. One of the studies by Nguyen et al., [99], infers the performance of the membrane is a function of the mass transfer coefficient in HF tubes. Hence, overall analysis of the mass transfer coefficient is crucial for the high performance of the membrane modules. This is directly linked to the performance of water transport, and it has been demonstrated that ANN can predict the transfer coefficients of water transport with a correlation coefficient of 0.99. A deep neural network and an ensemble of regression trees were used by Stel'makh et al., [100] to create a model that predicted the mechanical properties of lightweight fiber-reinforced concrete, which is widely used in the construction sector. They obtained 0.98% to 6.62% mean absolute percentage error (MAPE), 0.17 to 0.89 root mean square error (RMSE), and 0.15 to 0.73 mean absolute error (MAE) using a neural network. In contrast, it ranged from 0.11 to 0.62 MAE, 0.15 to 0.80 RMSE, and 1.30% to 3.4% MAPE for an ensemble of regression trees. Two techniques were found to be efficient in finding the mechanical strength of heterogeneous hard-to-predict material by establishing the key role of the distribution of fibers and the number of fibers in developing mechanical strength.

The prediction and improvement of HF membrane performance measures, such as flow, rejection rate, and fouling resistance, might be improved by utilizing data-driven analytical methodologies, which could help us better understand the relationship between membrane properties and their performance. Shahouni et al., [101] developed ML models, such as ANNs and SVMs, have been employed to predict key performance metrics like water flux and fouling behavior, demonstrating superior accuracy compared to traditional methods. The paper by Ismael et al., [102] focused on predicting flux pressure in vacuum membrane distillation using a hybrid machine learning model (SVR–SHO), achieving high accuracy (R=0.94) compared to other models, thus enhancing prediction capabilities for membrane performance metrics like flux.

4.3. Process optimization

ML techniques optimize membrane fabrication processes by analyzing vast datasets and identifying critical parameters for enhancing membrane quality, uniformity, and performance. In the study performed by Liu et al., [103] features were categorized and were used to predict the performance of membrane filtration applications using ML. For the phase inversion technique- types of substrates, exposed time, relative humidity, thickness of the wet membrane, temperature for membrane casting, temperature of the coagulation bath, and the non-solvent in the coagulation bath were considered as features for membrane fabrication. The thickness, porosity, surface contact angle, and roughness were considered features of membrane structure. Transmembrane pressure (TMP) and material separation parameters including partial charge, molecular weight, radius, and feed flow concentration are features that are necessary for functioning. In their study, they mainly used PES, PVDF, and PSF polymers and their features are molecular weight, bulk density, melting temperature, heat detection temperature, and concentration of the polymer in the casting solution.

There is limited study in optimizing membranes to enhance performance. Fetanat et al., [104] created an ANN-based machine-learning model that considers seven input variables: contact angle, solvent type, solvent concentration, filler size, average filler concentration, and polymer type. The output variables are solute rejection, pure water flux, and flux recovery. It was observed from the study that solvent concentration was found to be the important factor and filler concentration, and average filler size were found to be the least significant factor. The application of the ML technique for the UF process involving the xylose reductase enzyme separation mechanism has been explained by Reza Salehi et al., [105]. Using the boosted regression tree (BRT) model, they could predict membrane flux and xylitol production. Using ML algorithms like ANN and SVM models, the membrane permeability in membrane rotating biological contractors (MRBCs) for wastewater treatment has been optimally attained by Waqas et al., [106]. These models, which consider different operating characteristics such as disk rotating speed, hydraulic retention time (HRT), and sludge retention time (SRT), have proved very helpful in forecasting and improving membrane permeability. The MRBC system, integrating membrane filtration and a rotating biological contactor, has shown promising results in terms of membrane fouling optimization and sustainable treatment processes, aligning with the principles of ecological evolution and environmentally friendly practices.

4.4. Fault detection and quality control

ML algorithms can detect anomalies, defects, or inconsistencies in the manufacturing process, ensuring the production of high-quality polymer HF membranes and reducing wastage. Hence data-driven approach of ML enables researchers to extract insights from complex experimental and simulation data, facilitating a deeper understanding of the structure-property relationships within polymer HF membranes. A case study used a membrane bioreactor to predict the TMP, required for assessing fouling conditions Kovacs et al., [107]. They used more than 80,000 samples to train and test data-driven models to predict TMP. In another study of fault detection done by Zadkarami et al., [108], they designed a framework using classification methods such as multilayer perceptron neural network (MLPNN), support vector machine (SVM), and principal component analysis (PCA). Results for the MLPNN classifier showed the highest fault detection accuracy of 99.7%. The framework developed can be well utilized for membrane monitoring systems towards quality control and surveillance mechanisms. Continuous monitoring of UF system is essential for the proper operation of the membrane and hence there will be ease of flow of filtered flux and hence lower fouling rate. Shim et al.,[109] developed deep learning models based on CNN and LSTM to evaluate the turbidity of water since turbidity is key feature of water impurity. Further, they were able to find precise results with the addition of variation mode decomposition (VMD) based intrinsic mode functions (IMFS). A study related to protein fouling by Tanudjaja et al.,[110] forecasted considering 10 input variables by choosing RF model and neural network (NN) Their study inferred membrane pore size, TMP have a significant contribution towards fouling and membrane configuration was found to be the least significant factor.

Recent innovations in ML assisted fault detection and quality control in membrane manufacturing processes have significantly enhanced defect recognition and process monitoring. These developments make use of deep learning and computer vision methods to increase the precision and effectiveness of detecting flaws and errors at every stage of the production process. Kellermann et al. [111] used an autoregressive model with a neural network to develop a ML method for defect identification in multi-stage manufacturing. With a true positive rate of 0.79 and a false positive rate of 0.07, the approach made it possible to discover errors without the need for specialized quality checks at each step. An industrial defect detection system addressing a range of quality issues was tested by Mir et al., [112], who found that it performed well in terms of precision (93–96%), recall (92–95%), and F1-scores (93–95%). The system's dependability and usefulness in industrial quality assurance are highlighted by macro, weighted, and micro averages of about 94%, which show robustness across defect classes.

Static ML models face significant challenges when applied to dynamic membrane processes and real-time monitoring. The prediction reliability of methods like neural networks, which learn input-output mappings from preset datasets, decreases as system behaviour deviates from the training data [113]. This temporal drift problem becomes crucial in systems that change quickly and require constant feed-back control. Membrane processes, which are controlled by intricate biological and physicochemical interactions, are prime examples of settings in which static machine learning models find it difficult to represent the dynamic nature of fouling and changing process conditions [114]. With root mean squared errors reported as low as 0.05% for chosen parameters, data-driven systems can provide remarkable accuracy under stable settings, but their efficacy declines as operating conditions change. Adaptive machine learning techniques that integrate model-independent control robustness with ML's global feature learning capabilities are the answer [115].

ML-based designs allow tailoring polymer HF membranes for specific applications, such as water purification, gas separation, and biomedical devices, by optimizing membrane properties to meet the desired performance metrics. Optimization in the case of the conventional approach requires extensive trial-and-error experimentations resulting in wastage of materials and resources.

On the other hand, ML allows researchers to develop suitable membrane materials and structures by minimizing the need for extensive trial-and-error experimentation. Hence by harnessing the capabilities of machine learning, researchers and engineers in polymer HF membrane science and engineering can achieve faster innovation, more precise predictions, and optimized membrane performance, ultimately advancing a wide range of industrial, scientific, and environmental applications.

Developing dynamic ML models for membrane applications is hampered by issues such as data integration, limited interpretability, and low data quality. Researchers and data scientists must work together more closely to improve model and descriptor selection, since studies on membrane design point out problems such poor data mining, a lack of material descriptors, and inappropriate model selection [84]. Similarly, establishing trustworthy structure-property connections and design principles when using data-driven approaches to MOF-based membranes presents challenges that can be addressed by integrating atomic-level simulations to improve accuracy and efficiency and by improving machine learning techniques [116]. Interdisciplinary collaboration among machine learning specialists, materials scientists, and engineers holds substantial potential for bridging existing gaps in materials research. Combining machine learning, materials science, and engineering into interdisciplinary partnerships speeds up the discovery of new materials, improves manufacturing, and enhances predictive modelling, all of which lead to useful technological applications. Through pooled knowledge and outside resources, these collaborations improve data interpretation, model building, and experimental design while also encouraging innovation in sustainable materials [117,118].

The automation of membrane design and production through machine learning (ML) techniques presents significant environmental and economic impacts. By enhancing membrane efficiency and performance, ML can lead to more sustainable practices in energy production, gas separation, and water treatment, ultimately contributing to global environmental goals.

Overall, machine learning plays a crucial role in enhancing the efficiency and predictability of membrane separation processes across various industries, offering valuable insights for future membrane design and optimization. Table 8 covers the literature referred to regarding recent advancements and applications concerning membrane technology for separation applications.

Table 8. Literature survey of current advancement in membrane technology

Ref	Insight	Key parameters	Outcome
[68]	Modelling and optimization of HF membranes for CO2 separation from CH4 done; MLR, SVR, DTR employed for regression; GA and PSO used for optimization.	Feed pressure, temperature, membrane selectivity, permeability of CO2 and CH4, flow rates.	SVR and DTR outperformed MLR Feed flow 3.333 x 10^{-5} (m^3/s), T_f =30℃ P_f = 5bar, Xco2 =0.06.
[69]	In green house environment, HF membrane used; CO2 concentration obtained; regression analysis done to estimate the relation between temperature and CO_2 variation.	Feed pressure, operating pressure, and operating temperature	Without CO_2 supply: R^2= 0.170 With CO_2 supply: R^2= 0.628 coefficient of determination 68.4%.
[70]	Machine learning model using Random Forest (RF) and Deep Neural Network (DNN); to compute gas permeabilities and selectivity.	Experimental gas permeabilities of databases PolyInfo and MSA	DNN gave better results in comparison to other techniques by having R^2 value of ~0.9.
[71]	Hybrid modelling was developed; operating variable correlation found; Projection to latent structures (PLS), ANN, PCA with ANN employed; %rejection and %adsorption of micropollutants calculated.	Solvent viscosity, pure solvent permeability, solvent density, solvent molar volume, solvent dielectric constant, solvent dipole moment, solvent geometric radius, solvent	Not mentioned

Ref	Insight	Key parameters	Outcome
		ellipsoidal ratio, sol/membrane surface tension, sol/membrane solubility, membrane Molecular weight cutoff (MWCO)	
[72]	ML model designed; physical properties predicted; ANN employed;	Connectivity indices used for predicting molar volume, Fedors-type cohesive energy, Krevelen-type cohesive energy	Physical properties predicted by ANNs with R^2 scores > 0.82.
[73]	ML model trained; experimental permeability dataset for six gases utilized; permeability predicted using Gaussian process regression (GPR) method	Diffusivities, solubilities, and permeabilities for six gases - methane, carbon dioxide, helium, hydrogen, nitrogen, and oxygen- 500 polymers for each gas.	R^2 value was found to be 0.8 between a predicted and actual set.
[74]	Machine learning model applied; glass transition temperature (Tg) predicted based on different structure representations as training sequences; 79 different ML models applied	Different polymer representations (Morgan fingerprint) from PoLyinfo, Polymer Property Predictor and Database, CROW Polymer Properties Database	SVM model resulted best with R^2 value 0. 865.Comparison of experimental and simulation resulted R^2 =0.90, MAE=28.13, RMSE=34.28
[75]	ML model created; relationship between fabrication conditions and membrane properties investigated; Water permeability, removal efficiency, and related indices represented membrane performance.	Fabrication conditions (11 variables), operational conditions (6 variables), membrane properties (4 variables)	For water permeability, removal efficiency, and flux decline ratio, the R^2 value was greater than 0.78. Membrane performance is greatly impacted by additive loading (>1.0 wt%).
[76]	A computational fluid dynamic (CFD) and mathematical modelling on Direct contact membrane distillation (DCMD) performed; flux performance, temperature and concentration polarization were predicted.	Inlet feed temperature, membrane thickness, porosity, pore size, and feed flow rate	Mass transfer coefficients are calculated for different ranges of Khudsen numbers. Membrane flux increases with reduced thickness, increased porosity, and pore size.
[77]	A mathematical model was developed; ANN employed to estimate the water transport in the HF membrane in a vehicle humidifier.	Operating temperatures, system pressures, inlet flow rates, and inlet relative humidity	ANN model demonstrated good prediction capability of water transport in a humidifier with a correlation coefficient (R^2=0.99)
[78]	A DNN and ensemble regression trees are used in this model to predict the properties of lightweight fiber-reinforced concrete.	Amount and distribution of fiber	Coefficient of determination ranged 0.94-0.99. RMSE, MAE, and MAPE were used to gauge DNN's accuracy. Both methods demonstrated excellent effectiveness.

Ref	Insight	Key parameters	Outcome
[79]	A regression analysis was considered; considered 1895 data vectors for water purification of micro/ultra/nanofiltration.	features for base polymer (5 parameters), features for the membrane structure (4 features) features for the membrane fabrication (7 parameters)	The coefficient of determination was 0.79 to.85 for regression models, an area under the curve (AUC) was 0.94 to 0.97 for classification.
[80]	ML model was developed; feed-forward ANN and Bayesian regularization algorithm used to evaluate solute rejection, flux-recovery, and pure water flux as output variables.	7 input variables: polymer concentration, polymer type, filler concentration, average filler size, solvent concentration (in the dope solution), solvent type, and contact angle	ANN model was the effective model for solute rejection, pure water flux, and flux recovery with R^2 values 0.93,0.91 and 0.92 respectively.
[81]	Two types of ML models were designed; one using a neuro-fuzzy inference system based on grid partitioning and another employing a boosted regression to separate enzymes during xylitol production in terms of membrane permeability (membrane flux) and xylitol concentration as output.	transmembrane pressure, crossflow velocity, and filtration time	The coefficient of determination for membrane flux and xylitol concentration were 0.994 and 0.967, respectively. Boosted regression tree model outperforms adaptive neuro-fuzzy inference
[82]	ML model designed; fouling analysis in MRBC; SVM and ANN to find membrane permeability. Bayesian, grid search, and random search optimization algorithms used.	Disk rotational speed, hydraulic retention time (HRT), sludge retention time (SRT)	ANN with 13 hidden layers and SVM with Bayesian optimizer used. ANN model exhibited an R^2 value of 0.999 grid search 0.983 and SVM random search, which was 0.989.
[83]	Machine learning model developed; RF, ANN, and long-short term memory (LSTM) network employed; TMP at different stages of membrane bioreactor (MBR) predicted.	TMP, flow, flux and permeability	RF model performed best with R^2 value between 0.927 to 0.996. For ANN R^2 value ranged between 0.910 - 0.973 and for LSTM 0.878 to 0.915.
[84]	Framework-membrane fault detection; feature analysis algorithm based on wavelet used; MLPNN, SVM and PCA classifiers used.	Inlet flow rate, recirculation flow rate, permeate flow rate, inlet pressure, recirculation loop inlet pressure, recirculation loop outlet pressure, permeate, pressure, permeate tank pressure(level), temperature.	MLPNN was the best classifier with highest detection accuracy (99.7%) having a minimum percentage of false alarms.
[85]	Developed deep learning models; CNN and LSTM were used to remove colloidal particles.	Outlet turbidity, inlet pressure, outlet pressure, inlet temperature, inlet flow rate, outlet flow rate, NaOCl flow rate, and H_2SO_4 flow rate.	Coefficient of determination (R^2<0.9203), resulted in improved accuracy.
[86]	RF and NN model developed; performance measured using permeate flux and protein rejection	Protein type, protein concentration, membrane material, membrane pore size, membrane configuration, cross-flow velocity, TMP, Ph, salt content, steady state flux, protein rejection	Membrane material is concerned important for permeate flux and membrane pore size matters for protein rejection process.

5. Conclusion

This systematic review summarizes membrane technology and its applications in different fields. Applications include water purification techniques in a liquid medium, air purifiers in a gaseous medium, separators in textile industries, quality enhancers in dairy industries, and for dialysis and other applications in the biomedical sector. Depending on the application different types and configurations of membrane modules are used. But geometry and type of the membrane produced not only depend on the materials used, but they also depend on the operating conditions. Hence design of a membrane is one of the challenging things. There is a need to automate the membrane design by making use of available AI techniques. Hence the SLR also covers different studies on design techniques, simulation studies, and developing models by making use of ML techniques. Finally, the systematic survey procedures and the steps are illustrated with the help of the PRISMA diagram.

Author's contribution

Anupama B: Drafting original article, carrying literature study and reporting, formatting, generating artistic diagrams. Roopa B Hegde, Arun M Isloor: Conceptualization, planning, assisting in technical content writing, reviewing. Sneha Nayak: assisting in diagrams, reviewing. Muttanna Venkatesh: drafting, formatting

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