






Antibiotic removal in South African water using artificial neural networks and adaptive neuro-fuzzy inference system models: A review

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ABSTRACT

The growing occurrence of antibiotic residues in South African water systems poses serious environmental and public health risks, owing mostly to pharmaceutical discharge, agricultural runoff, and poor waste management. Conventional water treatment procedures frequently fail to properly remove these micropollutants, needing new predictive and analytical approaches. This review critically investigates the implementation of Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models to forecast and optimize antibiotic removal from South African water bodies. To the best of our knowledge, little or no research compares the models' respective performances in the context of the urban water cycle in South Africa. Therefore, this review elaborates on some of the pharmaceuticals (such as diclofenac sodium and tetracycline) that have been studied, as well as the challenges associated with their removal. It also emphasizes studies on modeling and predicting pharmaceutical removal from wastewater using ANN and ANFIS models. Additionally, this review considered the comparisons between ANN and ANFIS models in predicting the removal of emerging contaminants, as well as the challenges and limitations associated with these modeling techniques. The studies established that AI models achieved higher R^2 and lower error metrics compared to classical statistical or isotherm models.

1. Introduction

The global urban populace has been rapidly increasing; the metropolitan population in 2014 was ~54 %, and this percentage has been projected to rise to ~66 % in 2050 (Jensen and Wu, 2018). The population growth has brought about numerous negative effects on the environment, with water resources being the most affected by loss of quality and continuous degradation (Peña-Guzmán et al., 2019). The management of water resource quality has conventionally concentrated on nutrients, suspended particles, heavy metals, and human infections; however, emerging contaminants (ECs) have recently become a growing concern (Sutherland and Ralph, 2019). ECs are substances or materials for which there are either few or no recognized health standards but are thought to pose a real or potential environmental or human threat (Gomes et al., 2020). ECs are mostly industrial synthetic pigments,

dye-containing hazardous pollutants, micropollutants, endocrine disruptors, pesticides, medicines, hormones, and poisons (Khan et al., 2022). Approximately 200 distinct compounds have been discovered as ECs in the aquatic environment, with the most commonly recognized being pharmaceuticals, personal care items, insecticides, and flame retardants (Sutherland and Ralph, 2019). The presence of ECs in effluents contaminates the recipient water body (surface and underground water), making them unfit for potable and industrial use and with detrimental consequences on the ecosystem and public health (Viet and Jang, 2023).

In South Africa, pharmaceuticals are one of the highly detected ECs. This high detection could result from an increase in tuberculosis (TB) infection cases. TB has been reported to remain a global health concern, with South Africa ranking in the third position globally with the worst TB epidemic after China and India (Churchyard et al., 2014). Besides TB,

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further infectious diseases like pneumonia and diarrhea are common. These infections are mostly caused by weakened immunocompromised conditions brought on by Human Immunodeficiency Virus (HIV) infections, inadequate sanitation, and drug use, among other things (Izrah, 2024). Owing to the heightened susceptibility of patients with HIV and TB to other diseases, such as pneumonia, more antimicrobial medications are being given, which raises the total amount of pharmaceuticals used (Heidary et al., 2022). Drugs that are used to treat TB, HIV, and other related infections are highly consumed, which has led to an accumulation of these medicines in the aquatic environment (Dhedda et al., 2024).

Current wastewater treatment techniques rely heavily on statistical and multivariate data analysis methods, as well as intricate mathematical formulas and computations (You et al., 2017). These conventional approaches are primarily used to estimate uncertainty and assess the effectiveness of pollutant removal. However, they often involve tedious calculations and are prone to errors in prediction. Moreover, they depend on linear assumptions and manual calibration, which limit their adaptability to dynamic environmental conditions and emerging contaminants such as antibiotics (Sun and Sun, 2015). Despite their wide use, these conventional models struggle to accurately capture the nonlinear and complex interactions inherent in wastewater treatment processes. This limitation underscores the need for innovative techniques that can facilitate more rapid, accurate, and efficient prediction and modeling of antibiotic removal. Artificial intelligence (AI) has emerged as a powerful tool in environmental modeling due to its ability to handle complex datasets and uncover hidden patterns. AI techniques, particularly Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), have been widely applied in various aspects of wastewater treatment (Malviya and Jaspal, 2021). These models offer significant advantages over conventional methods by minimizing computational complexity, improving prediction accuracy, and adapting to changing conditions. However, as far as it can be ascertained, there has been little or no research comparing the performance of ANN and ANFIS models in predicting the removal of antibiotics within the framework of South Africa's urban water cycle. This represents a critical gap in literature, especially considering the growing concern over pharmaceutical contaminants in urban water systems and the need for context-specific modeling approaches. Therefore, the present review aims to address this gap by elaborating on the types of pharmaceuticals that have been studied and the challenges associated with their removal. The major aspects of this paper gave the research significance, an overview of the study area, emerging contaminants in the urban water cycle, environmental and health concerns associated with pharmaceuticals in water, and challenges in treatment. Furthermore, AI application in contaminant removal prediction, challenges and future direction were highlighted.

1.1. Research significance

Despite growing concern over pharmaceutical contaminants in urban water systems, current wastewater treatment modeling approaches remain limited in their ability to accurately predict the removal of antibiotics. Conventional statistical and multivariate techniques are often constrained by linear assumptions, computational complexity and reduced adaptability to dynamic environmental conditions. These limitations hinder the development of efficient and responsive treatment strategies, particularly in regions like South Africa where data variability and infrastructure challenges are prevalent. This review advances the state of the art by introducing and comparing two AI-based modeling techniques, ANN and ANFIS, for predicting pharmaceutical removal efficiency. These models offer superior capabilities in handling nonlinear relationships, learning from complex datasets, and adapting to changing conditions, thereby overcoming the shortcomings of conventional methods. By synthesizing existing studies and evaluating the performance of ANN and ANFIS within the context of

South Africa's urban water cycle, this review provides a foundational understanding of how AI can be leveraged to enhance wastewater treatment modeling. The findings contribute to the broader knowledge base by identifying effective modelling strategies for emerging contaminants, guiding future research, and informing policy and operational decisions aimed at improving water quality and public health outcomes.

2. Overview of study area

South Africa is the southernmost country on the African continent. It has become a tourism destination since apartheid was officially abolished due to its diversified topography, beautiful natural surroundings, and rich cultural heritage (Vigne et al., 2024). Its surface area is approximately 1219,602 km², and it spans nine provinces: the Eastern Cape, the Free State, Gauteng, KwaZulu-Natal, Limpopo, Mpumalanga, the Northern Cape, Northwest, and the Western Cape. It extends latitudinally from 22°S to 35°S and longitudinally from 17°E to 33°E. The nations' boundaries are with Swaziland, Namibia, Botswana, Zimbabwe, and Mozambique. Southeast of the Mountain Kingdom of Lesotho is landlocked by South African territory. Approximately 1920 km southeast of Cape Town are the Prince Edward and Marion islands, which South Africa annexed in 1947 (Vigne et al., 2024). According to estimates using the most recent United Nations data, the South African population was estimated to be 64,104,804 million with an average growth rate of 1.44 % (World Population Review, 2024). Fig. 1 depicts the South African map with the nine provinces and a few key cities. The three main issues facing South Africa are inequality, poverty, and unemployment. South Africa has developed a National Development Plan 2030 in response to these pressing issues (Statistics South Africa, 2019). The potential for comprehensive growth that may end poverty and promote sustainable development is present in South Africa's human population and natural resources. Sustainable management of water resources, access to clean water, and sanitation are all necessary to unlock economic growth and productivity (United Nations, 2018). Therefore, to attain the sustainable development goals (goal 6) for Vision 2030 in South Africa, it is necessary to X-ray the state of the urban water cycle for emerging contaminants in the water resources and propose a sustainable solution to these pollutants.

3. Emerging contaminants in the urban water cycle

Various pharmaceutically active compounds have been discovered in water since the 1990s when pharmacological pollutants were first discovered in aquatic systems (Mosharaf et al., 2024). The amount of antibiotics present in influent and effluent samples from WWTPs varies greatly by region, varying from levels lower than the limit of quantification (LOQ) to hundreds of thousands of nanograms per liter (Jiang et al., 2024). Several African nations, for example, South Africa, Cameroon, Egypt, Kenya, Ghana, Nigeria, and Tunisia, have looked into the consequences of antibiotics in ecological waters (Waleng and Nomngongo, 2021). EC concentrations in portable water resources from various zones in South Africa varied from 0 to 330 ng/L in the East zone, 0.03 to 220 ng/L in the North zone, and 0 to 10 ng/L in the South zone, no research has been published from the West zone. The North zone's highest concentrations of Terbutylazine (220 ng/L), Atrazine (160 ng/L), and Carbamazepine (150 ng/L) have been detected. High amounts of these three substances were also found in the East zone, but carbamazepine was the most abundant (330 ng/L), followed by atrazine (180 ng/L) and terbutylazine (60 ng/L). Terbutylazine concentrations in the South Zone were as high as 10 ng/L (Gani et al., 2021). The widespread use of antibiotics in human health, animal husbandry, aquaculture, and agriculture has also been researched and discussed in the literature as a factor in their environmental prevalence (Jiang et al., 2024). Fig. 2 shows the trend in African countries and their contribution to ecological pharmacological surveillance.



Fig. 1. South Africa map with the nine provinces and some major towns. (Permission not required: CC BY-SA 3.0). Source: <https://www.bing.com/images/search?q=Free+Printable+Map+of+South+Africa&FORM=RESTAB>. Accessed date September 9, 2024.

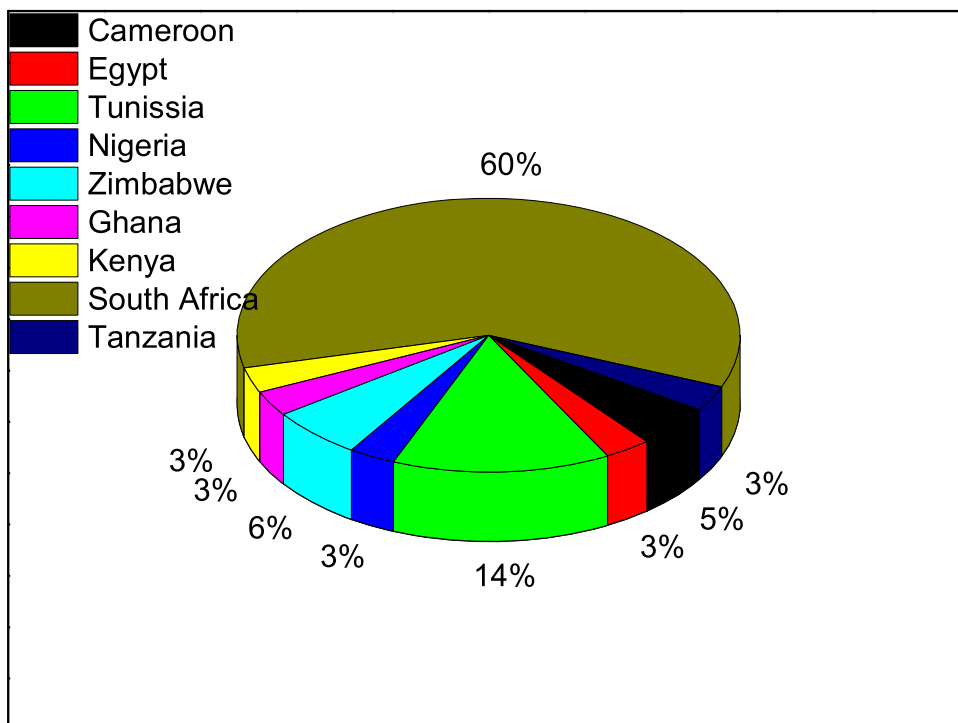


Fig. 2. Selected African nations’ respective scientific contributions to environmental water pharmaceutical monitoring (Waleng and Nomngongo, 2021) CC BY-NC–ND 4.0 (<https://creativecommons.org/licenses/by-nc-nd/4.0/>).

The scant information provided regarding the pharmaceutical's occurrence indicates that a thorough comprehension of the idea of water pollution in African nations is still a long way off. Although South Africa has produced the most articles in this field, their prevalence and removal in rural regions and seawater have received less attention (Waleng and Nomngongo, 2021).

3.1. Type and sources of emerging contaminants

Different types of ECs vary from regularly utilized products, for instance, cosmetics, pharmaceuticals, plasticizers, and flame retardants have been identified. The list is constantly growing with many more compounds reported to be available in the environment (Pereira et al., 2015). Pharmaceuticals, personal hygiene items, insecticides, and flame retardants are the most often found emerging pollutants in aquatic environments; over 200 distinct chemicals have been identified to date (Sutherland and Ralph, 2019).

3.2. Pharmaceuticals as emerging contaminants in the urban water cycle

Environmental contamination from pharmaceuticals and personal care products (PPCPs) usually arises from the inappropriate disposal of drugs, cosmetics, and veterinary antibiotics (Keerthanan et al., 2021). The detection and measurement of several pharmaceutical chemicals in ambient water, wastewater, and potable water have been made possible by technological advancements and analytical techniques (Caban et al., 2015). The presence of pharmaceuticals and related products needs to be monitored carefully because they contain substances that can be harmful to both people and the environment, like sulfamethazine, diclofenac, ibuprofen, salicylic acid, and many others (Sundaraman et al., 2022; Tijani et al., 2016). Many pharmaceuticals are biologically degraded to produce metabolites that still need to be analyzed (Fatta-Kassinos et al., 2011a). Since these pharmaceuticals affect humans and aquatic organisms negatively and are difficult to decompose completely, they lead to the pollution of soil and water as ECs (Pal et al., 2014). The incessant disposal of PPCPs into aquatic ecosystems allows them to remain in the environment despite their short half-lives (Ziylan-Yavas et al., 2022). Pharmaceuticals have been observed to occur as ECs in some nations of late, which has caused the scientific community and the general public to express deep concern. Despite the extensive use of pharmaceuticals, little is known about their environmental presence, particularly in African nations (Agunbiade and Moodley, 2014). However, in recent years, studies have been made in South Africa on the emerging contaminants in the marine environment, with lower institutional and academic research outputs that can be attributed to inadequate infrastructural facilities for ECs investigation in South African laboratories (Gani et al., 2021).

3.2.1. Pharmaceutical sources and pathways in the urban water cycle

Many medications target species and interact with particular systems to change physiological functioning and generate therapeutic effects (Overturf et al., 2015). However, they are being released into ambient aquatic environments with negative consequences on non-target receptors (Fabbri and Franzellitti, 2016). Although many pharmaceuticals break down quickly, their constant and prevalent consumption has led to their quasi-continuity in aqueous media (Li et al., 2017). Pharmaceutical substances can enter the aquatic environment through many routes and sources. The primary source can either be direct or indirect release from industrial and medical wastewater (Parra-Saldivar et al., 2021). The municipal sewage treatment plants also do not effectively remove trace pharmaceuticals and thus they may be discharged into the environment (Chavoshani et al., 2020). The continuous release of wastewater from aquaculture, livestock dung, and agricultural pollution are other significant pathways of pharmaceuticals in the environment (Buono et al., 2012; Zhang et al., 2016). A summary of the many pharmaceutical product sources found in aquatic environments is shown in

Table 1

An overview of different sources of pharmaceuticals in the aquatic environment.

Sources of pharmaceuticals	Description
WWTPs	Pharmaceuticals can enter surface waters through wastewater treatment systems after being excreted by humans and animals (Voulvoulis et al., 2015).
Agricultural Runoff	Pharmaceuticals used in veterinary medicine, such as antibiotics can be present in animal waste and agricultural runoff which may reach water bodies (Buono et al., 2012).
Aquaculture	Pharmaceuticals used to treat diseases in aquatic systems can enter surrounding waters through discharges and waste from fish farms (Zhang et al., 2016).
Pharmaceutical manufacturing	Residues from pharmaceuticals that are disposed of in landfills or waste disposal sites can leach into groundwater, potentially reaching nearby water sources (Nyaga et al., 2020).
Landfills and solid waste disposal	Pharmaceuticals that are disposed of in landfills or waste disposal sites can leach into groundwater (Nyaga et al., 2020).
Direct disposal	The prevalence of pharmaceuticals in water bodies can be attributed to the habit of flushing unused medications down the toilet or sink (Dar et al., 2019).
Hospital and healthcare facilities	Pharmaceuticals may leak into the environment as a result of hospitals and other healthcare facilities disposing of medical waste improperly (Kadam et al., 2016).
Storm Runoff	Rainwater can wash pharmaceutical residues from streets and other surfaces into stormwater drains and eventually into water bodies (Saifur and Gardner, 2021).

Table 1. Pharmaceutical residues have also been discovered in fruits and vegetables and may have adverse effects on humans (Thompson and Darwish, 2019).

As evident from Table 1, it is obvious that medications and their metabolites are excreted in urine, feces, or manure. They might go through a partial breakdown, biodegradation, or even stay in their original form. The release of unabsorbed pharmaceuticals into the sewage system, the flushing of unwanted medicines down the toilet or sink, the emission of veterinary drugs into fields by farm animals, and inappropriate commercial disposal techniques are some of the ways they get into the urban water cycle. Since most pharmaceuticals have low volatility, they tend to spread throughout the environment as an aqueous solution or suspension (Fatta-Kassinos et al., 2011b). Fig. 3 illustrates how pharmaceutical substances both for human treatment and animal therapy enter the environment. From the dispensary of pharmaceuticals, it can be noted that the pharmaceuticals are excreted from animals and humans to reach the WWTPs (Madikizela and Chimuka, 2017). They are also disposed of as part of hospital waste that makes its way to the landfills and eventually percolates into the groundwater. In addition, direct discharge of aquaculture wastewater from fish farms containing pharmaceutical remains would result in them reaching the surface water during storm runoffs.

3.3. Types of pharmaceuticals detected in the urban water cycle

Various kinds of medications have been found in aquatic environments. Medicines used to treat cancer, such as lipid regulators, diuretics, anti-epileptics, beta-blockers, steroids, and related hormones; anxiolytics; non-steroidal anti-inflammatory medications; analgesics and proton pump inhibitors; are some of the groups to which these identified pharmaceuticals belong (Ngqwala and Muchesa, 2020; Ngumba et al., 2016). The commonly identified pharmaceuticals in South African water include analgesics, anti-inflammatories, antiretrovirals and antibiotics (Ngqwala and Muchesa, 2020).



Fig. 3. Pharmacological pathways in the urban/non-urban water cycle (Castillo-Zacarias et al., 2021). Permission has been granted by the authors.

3.3.1. Analgesics and anti-inflammatory drugs

Analgesic medications are used to treat or reduce pain, whereas anti-inflammatories are used to treat or minimize swelling and inflammation (Ngqwala and Muchesa, 2020). In South Africa, the commonly applied analgesics and anti-inflammatories are ketoprofen, aspirin, diclofenac, naproxen, ibuprofen, and acetaminophen (paracetamol) (Madikizela et al., 2020). An investigation on the prevalence of specific drugs in the water and sediment of the Umgeni River in KwaZulu-Natal, South Africa, has shown that ibuprofen was detected in extreme concentrations than other non-steroidal anti-inflammatory drugs (Matongo et al., 2015). The investigation found that effluent samples from the river connected to WWTP had ibuprofen levels as high as 12.94 $\mu\text{g/L}$ (Matongo et al., 2015). The higher concentration of ibuprofen in the effluent samples suggests the ineffectiveness of the WWTP in removing ibuprofen (Matongo et al., 2015). Another study was carried out in the same province to track the concentrations of diclofenac, naproxen and ibuprofen in a river and WWTP close to Kwazulu-Natal, Durban city in South Africa. The study found that the concentrations of naproxen was 6.84 $\mu\text{g/L}$, ibuprofen was 19.2 $\mu\text{g/L}$, and diclofenac was 9.69 $\mu\text{g/L}$. Notably, ibuprofen had the greatest concentration (Madikizela and Chimuka, 2017). The highest quantities of Naproxen, Ibuprofen, and Diclofenac found in WWTP effluent samples were 14.4 $\mu\text{g/L}$, 67.9 $\mu\text{g/L}$, and 23.5 $\mu\text{g/L}$, correspondingly (Madikizela and Chimuka, 2017). According to a study conducted in the Northwest region of South Africa, the highest concentration of ibuprofen (13.7 $\mu\text{g/L}$) was found in the WWTP effluent (Kanama et al., 2018). The inference from these studies confirmed the presence of pharmaceutical remains in significant amounts in the water body of the province.

3.3.2. Antiretroviral drugs

Antiretroviral therapy, also referred to as ARV therapy, consists of a

blend of nucleoside reverse transcriptase inhibitors, non-nucleoside reverse transcriptase inhibitors, protease inhibitors that block different viral targets and authorized integrase inhibitors for patients with HIV who are virally resistant (Madikizela et al., 2020). Additionally, a mixture of medications is administered to stop mother-to-child transmission (Shah et al., 2018). In South Africa, about 8.45 million persons are HIV positive as presented in 2022 statistics (Nabeemeeah et al., 2024). Based on a previous study conducted and published, ARV drug detection was reported in the KwaZulu-Natal, Gauteng, and Western Cape water resources. The ARV drugs lamivudine, raltegravir, maraviroc, nevirapine, ritonavir, saquinavir, tenofovir, zalcitabine, efavirenz, emtricitabine, didanosine, indinavir, lopinavir, and zidovudine have all been observed in aquatic environments in South Africa (Ngqwala and Muchesa, 2020). Emtricitabine is the highest detectable ARV drug from influent samples of a WWTP, with a concentration of 172 $\mu\text{g/L}$ (Mosekiemang et al., 2019). In another related study, emtricitabine concentrations in surface water samples were as low as 0.013 $\mu\text{g/L}$. Efavirenz is the most commonly encountered antiviral drug in marine ecosystems in South Africa; it has been detected as high up to 140 $\mu\text{g/L}$ in Durban WWTP effluent samples (Mtolo et al., 2019). The lowest recorded efavirenz values, ranging from 0.002 $\mu\text{g/L}$ to 2.45 $\mu\text{g/L}$, were found in surface waters (Mtolo et al., 2019; Rimayi et al., 2018). Given the current situation regarding pharmaceuticals in aquatic environments, it is essential to conduct continuous studies to optimize water remediation techniques for enhanced national, provincial, regional, and local legislation. Understanding the approaches to lowering the dangerous concentrations of medications in the environment requires collaboration between stakeholders, producers, authorities, veterinarians, pharmacists, and consumers.

3.3.3. Antibiotics

In South Africa, antibiotics have been used extensively for both prophylactic and therapeutic purposes. Additionally, approximately 80 % of therapeutically significant antibiotics are also utilized for domestic animal, cattle, and agricultural uses (Tucker et al., 2022). The high consumption rate of antibiotics in South Africa can also be attributed to heightened cases of ailments for example cholera, meningitis, gonorrhoea, malaria, typhoid and TB that are connected to drug-resistant pathogens (Laxminarayan et al., 2013). Antibiotic-resistant bacteria have emerged as a result of the widespread use of antibiotics in both humans and animals, which further complicates the treatment of diseases (Mulamattathil et al., 2014). Antibiotic-resistant bacteria and genes are produced when antibiotics are present in the environment, and they both lower the possibility of treating bacterial infections in humans and animals (Ncibi and Sillanpää, 2015). The issue of antibiotic contamination of water sources has been extensively studied, solely focused on WWTP effluents. Many low- and middle-income nations, including South Africa, have reported an increase in the usage of antibiotics (Ngqwala and Muchesa, 2020). Some studies have been conducted on South African WWTPs and surface water to assess the occurrence of antibiotics. In one of the studies, a high concentration of sulfamethoxazole at 59.28 µg/L was noticed in the effluent of the WWTP of the Northern water works in Durban (Matongo et al., 2015). Another study detected ciprofloxacin at an influent concentration of 27 µg/L and effluent of 14 µg/L of a WWTP in KwaZulu-Natal (Agunbiade and Moodley, 2014). Tetracycline has also been detected at an extreme concentration of 45.38 µg/L in influent samples and 3.22 µg/L in the effluent samples from two hospital WWTPs in the Northwest province (Kanama et al., 2018). Other antibiotics detected in WWTPs include azithromycin, ofloxacin, norfloxacin and erythromycin with concentrations <10 ng/L (Ngqwala and Muchesa, 2020). Another study examined genes and bacteria with antimicrobial resistance in raw and untreated water throughout four seasons. On chromogenic R2A medium, 203 heterotrophic bacterial isolates were obtained, and their susceptibility to twelve antibiotics was tested (Ateba et al., 2020). Most of the isolates could absorb ciprofloxacin, erythromycin, and neomycin, but they were resistant to β-lactam and trimethoprim antibiotics (Ateba et al., 2020). The negative effects of these materials on the environment can never be over-emphasized. Hence, there is a need for continuous research for innovative approaches to the issues of antibiotic residues in the environment for a more holistic solution.

4. Environmental and health concerns associated with pharmaceuticals in water

PPCPs come in various types based on their intended use and nature. Drugs often consist of lipid regulators, blockers, sex hormones, neurostimulants, cytostatic medications, and non-steroidal anti-inflammatory drugs (NSAIDs) (Alshamsi et al., 2022). On the other hand, PPCPs contain UV protection filters, insect repellents, fungicides, disinfectants, and preservatives. >4000 PPCPs have been used on humans and animals (Khalid and Abdollahi, 2021). Medicines used to treat cancer, such as diuretics, anti-epileptics, beta-blockers, lipid regulators, steroids, and related hormones; anxiolytics; proton pump inhibitors, NSAIDs and analgesics are among the pharmaceutical residues found in aquatic environments (Ngqwala and Muchesa, 2020; Ngumba et al., 2016). The usually found pharmaceuticals in South African water are antibiotics, analgesics, anti-inflammatories, and antiretrovirals (Ngqwala and Muchesa, 2020). The depth of research on the toxicology of PPCPs is growing, and in the past few years, risk assessment has grown significantly. The organism's kind and stage, duration of exposure, temperature, and pollutant concentration all influence the degree of toxicity of PPCPs (Prichard and Granek, 2016). The emergence of bacteria resistant to antibiotics and antibiotic-resistance genes (ARGs), abnormal physiological processes and procreative impairment, an increase in cancer cases, and the possible toxicity of combined pollution are now the main

problems associated with PPCPs (Archer et al., 2017). Generally speaking, antibiotics are among the most effective and long-used medications available, and both veterinary and human antibiotics are widely found in aquatic habitats (Tucker et al., 2022). Numerous antibiotics have been detected in surface waters, drinking waters, groundwaters, animal wastewater, and sewage treatment plant (STP) effluents at different amounts, ranging from ng/L to a few µg/L. Various kinds of antibiotics, containing erythromycin, ofloxacin, lincomycin, sulfamethoxazole, and rotifers, were tested at varying nutrient levels in aquatic organisms, such as fish, bacteria, algae, and rotifers. The findings showed that at mg/L levels, antibiotics could result in serious adverse responses. According to an environmental risk evaluation, 20 % of 226 antibiotics were found to be extremely harmful to *Daphnia*, and more than half were poisonous to fish. Antibiotics cause extreme toxicity, impairment to the antioxidant system, and suppression of photosynthesis and cell development in algae. Algal cell development, chlorophyll concentration, and photosynthetic activity are all decreased by ofloxacin, which also affects the physiological functions of the algae's natural photochemistry and antioxidant system (Li et al., 2022). Farmland that has been treated with hazardous manure may see a fall in production if antibiotic concentrations in the soil prevent germination or lower biomass. Furthermore, exposure to antibiotic residues can alter the human microbiota and result in adverse health effects like allergic reactions, long-term injury, and changes in the digestive system's normal functions (Pineiro and Cerniglia, 2021). Aquatic ecosystems are one of the reservoirs and pathways via which antibiotic resistance spreads (Manaia et al., 2016). The capacity of bacteria to withstand an antibiotic's effects that they were once susceptible to is known as antibiotic resistance (Amarasiri et al., 2020). Through genetic mutation or the acquisition of ARGs, bacteria can develop resistance to antibiotics. Because WWTPs were unable to eliminate ARGs from WWTP effluent, they get into aquatic environments such as rivers and lakes. The environment could be prone to ARB and ARGs when recovered wastewater is used for recreational and agricultural irrigation (Slobodiuk et al., 2021). The exposure of humans to ARBs and ARGs is not just from intake of water but also via swimming, work exposure during agricultural irrigation, and eating fruit that has been irrigated with reclaimed water (Amarasiri et al., 2020). It has been demonstrated that traditional wastewater treatment technologies are poor at remediating wastewater linked to pharmaceutical residues, hence the application of AI technology is being explored for a general improvement in the waste management industry. Sophisticated methods need to be used to identify and quantify ECs, which are frequently present in trace quantities, in environmental matrices. High levels of sensitivity and selectivity are necessary to enable ECs to be identified and measured among a wide range of other chemicals (Li et al., 2024).

5. Challenges in the removal and treatment of pharmaceuticals

Concerns about the probable impacts of drugs on animals and human health have been brought up globally by their presence in the water cycle. The common medications are delivered to traditional WWTPs, where biological decomposition, adsorption, or stripping only partially removes them (Voulvoulis et al., 2015). This is because of the intricate structures of drugs and diverse chemical compositions (Ziylan-Yavas et al., 2022). The most often utilized and researched secondary processes in WWTPs are conventional ones, like trickling filters and activated sludge. The process of wastewater reclamation used in South Africa's urban cycle is shown in Fig. 4. However, these procedures are typically not intended to eliminate drugs, which leads to their release into surface waterways that receive them (Voulvoulis et al., 2015). Reverse osmosis membranes, nanofiltration, and sophisticated oxidation processes are a few examples of alternative treatment systems that have been explored for the selective elimination of pharmaceuticals (Ganiyu et al., 2015). Nevertheless, most of these techniques are associated with a substantial upfront cost, routine maintenance expenses, and a challenging

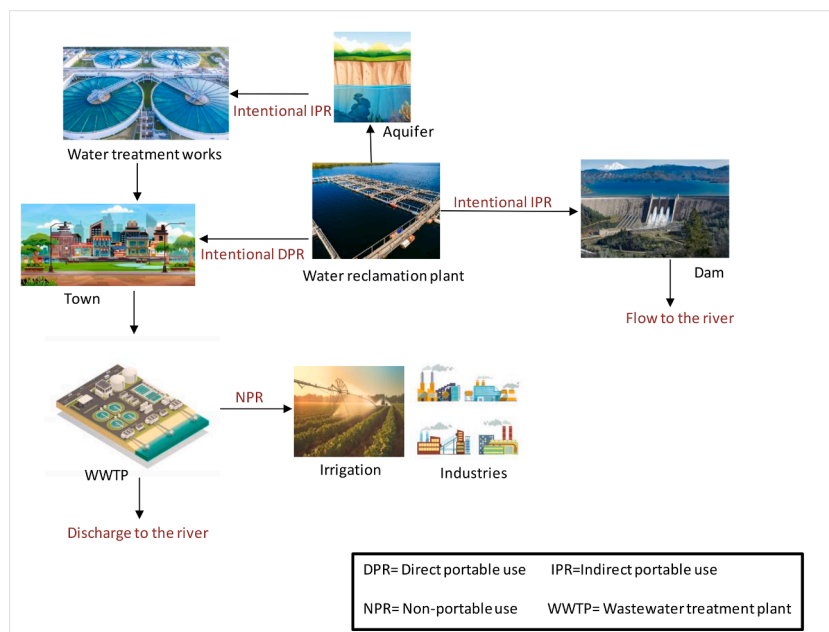


Fig. 4. The wastewater reclamation process used in South Africa's urban cycle.

wastewater treatment process (Shahid et al., 2021). Additionally, they may result in secondary pollution because of the oxidation by-products generated which may be even more hazardous than the original molecule (Ganiyu et al., 2015). Furthermore, PPCPs and endocrine-disrupting chemicals (EDCs) are typically not removed by physicochemical treatments such as flocculation and coagulation procedures (Shahid et al., 2021). Adsorption approaches are deemed better options than alternative methods for treating wastewater because they are easier to design and run and the process does not produce any unwanted contaminants.

The features of persistent organic pollutants (POPs) are also seen in PPCPs, and sewage treatment plants might not be able to get rid of them entirely (Al-Baldawi et al., 2021). The use of constructed wetlands (CWs) is now being considered in most studies for wastewater treatment as it is both economical and environmentally beneficial (Gorito et al., 2017). Mostly, CWs are intricate ecosystems consisting of local microbes, water, substrate, and plants (Gorito et al., 2017). *Phragmites australis* was employed in a study by Fadhil and Al-Baldawi (2019) to assess the capacity of the plant to treat total petroleum hydrogens (TPH) and chemical oxygen demand (COD) from refinery effluent using a free surface batch system. The findings demonstrated that *Phragmites australis* could withstand a contaminated environment and improved TPH biodegradation, with removal percentages of 98 % for TPH and 62.3 % for COD (Fadhil and Al-Baldawi, 2019).

6. Artificial intelligence techniques for prediction and modeling of emerging contaminants removal

Traditional statistical models, such as multiple linear regression (MLR) and response surface methodology (RSM), have long been used in wastewater treatment modelling due to their simplicity and interpretability (Qiu et al., 2025). However, these models often rely on linear assumptions and struggle to capture the complex nonlinear relationships inherent in pharmaceutical removal processes (Dikmen et al., 2025). They also require extensive manual calibration and are sensitive to missing or noisy data, which can compromise prediction accuracy. In contrast, AI techniques offer significant advantages in terms of both accuracy and computational efficiency. These models can learn from large datasets, adapt to changing conditions, and model nonlinear interactions without predefined equations (Dikmen et al., 2025).

Comparative studies have shown ANN and ANFIS consistently outperform traditional models in predicting pollutant removal, with correlation coefficients often exceeding 0.99, compared to lower values of MLR and RSM. Moreover, AI models reduce the need for complex experimental setups and manual tuning, making them more scalable and cost-effective for real-time applications. Overall, while traditional models provide foundational insights, AI techniques represent a more powerful and flexible approach for modelling and optimising pharmaceutical removal in wastewater treatment systems (Dikmen et al., 2025).

Wastewater treatment processes can be made simpler and more efficient with the help of AI, a potent instrument (Malviya and Jaspal, 2021). Because AI techniques have a significant capacity for reasoning, adaptability, modeling, and prediction, they have been applied predominantly in urban water resource planning (Xiang et al., 2021). Support Vector Machine (SVM), decision trees (DTs), fuzzy logic-fuzzy inference systems (FL-FIS), ANFIS, expert system (ES), ANN, model tree (MT), Random Forests (RF) and Bayesian network (BN) are among the frequently used AI techniques for modeling wastewater treatment (Behera et al., 2024; Nagpal et al., 2024). AI techniques are predicated on models and algorithms that are used to create computer systems that can learn from data, draw inferences, and forecast qualities of interest while carrying out tasks without direct guidance (Taoufik et al., 2022). The main aim of AI is to create predictive models that can accurately forecast or make judgments based on data-driven learning (Alprol et al., 2024). AI is an effective means for evaluating intricate wastewater treatment systems and enhancing water resource quality (Zhang et al., 2023).

In the context of pollutants removal, such as pharmaceuticals from wastewater, ANN and ANFIS are particularly well-suited due to their superior ability to model nonlinear, uncertain, and dynamic systems (Tran and Nguyen, 2024). Wastewater treatment involves complex interactions among chemical, biological and operational parameters, which ANN and ANFIS can effectively capture. ANN excels in learning intricate patterns from large datasets without requiring prior assumptions about data distribution, while ANFIS integrates the learning capabilities of ANN with the reasoning power of fuzzy logic, making it highly adaptable to systems with imprecise or incomplete data (Tran and Nguyen, 2024). Although other AI models, such as SVM and RF, are also widely used, they present certain limitations in this context. SVMs, while robust for classification tasks, often require careful kernel

selection and hyperparameter tuning to handle nonlinear regression problems, which can be computationally intensive. RFs, though interpretable and resistant to overfitting, may not capture subtle nonlinear dependencies as effectively as ANN and ANFIS. Furthermore, comparative studies have shown that ANN and ANFIS outperform classical models in terms of prediction accuracy and adaptability, especially in systems with stochastic or nondeterministic inputs. These strengths make ANN and ANFIS more suitable for modeling pharmaceutical removal in wastewater treatment, where precision and flexibility are critical.

6.1. Overview of artificial neural networks and adaptive neuro-fuzzy inference system models

The biological neural networks (BNNs) seen in live brains serve as the model for ANNs, which are intelligent learning instruments (Hasson et al., 2020). ANNs presently are the only models that achieve behavioral performance close to that of humans and can offer surprising understandings of the strengths and weaknesses of the direct-fit process (Hasson et al., 2020). They rely on a group of interconnected nodes known as artificial neurons or units, which mimic neurons in a biological nervous system. This makes them comparable to BNNs (Hasson et al., 2020). An artificial neuron receives input from multiple neurons, combines it, and then sends a signal to other artificial neurons that are linked to it. Usually, each artificial neuron's output represents a nonlinear function of its inputs. Artificial neurons are connected by weights that are changed as learning progresses. One such method is the backpropagation algorithm, which is based on reward signals or supervised feedback (Hasson et al., 2020). ANN models have been extensively used in several fields and studies usually for optimization, prediction and automation (Malviya and Jaspal, 2021). In a study conducted by Shahmansouri et al. (2021), the compressive strength of natural zeolite and silica fume-infused eco-friendly geopolymer concrete was successfully predicted using an ANN model. A similar study by Cabaneros et al. (2019), showcases the use of ANN models in the prediction of ambient air pollution. The ANN is also used in the medical field, for example, for effective diabetes prediction, whereby a model is developed to predict diabetes disease from the required data attributes (Bukhari et al., 2021). Recently, there has been an improvement in the ANN models that are being developed to increase the accuracy and effectiveness of these models. A study by Ahmed et al. (2019) produced a new ANN model that surpassed the performance of three empirical models that were reported in the literature. It was also able to predict the rate of penetration in drilling without the use of AI software (Ahmed et al., 2019). The ANN

procedure flow diagram is depicted in Fig. 5.

It could be seen from Fig. 5 that the first step in designing an ANN model, is with defining the input and output variables. The model architecture will then be developed followed by model training. The training is done using training data sets which are usually 70 % of the entire data used for modeling, and this is done by adjusting the model weight through backpropagation and gradient descent. Following this, the validation set was used to monitor the training process to avoid overfitting. The testing dataset can then be applied to estimate the model prediction performance. The correctness of the model is measured using matrices such as mean square error (MSE), root-mean-square error (RMSE), Pearson's relationship coefficient (R %), and the determination coefficient (R^2).

The most widely used neuro-fuzzy model for approximating extremely complicated nonlinear systems is ANFIS. The precision of ANFIS's exact fuzzy modeling and interpretability, which enhances its capacity for generalization, are the important features of ANFIS (Chopra et al., 2021). ANFIS modeling is based on the Mamdani or Takagi-Sugeno inference system and integrates the neural network with fuzzy logic in modeling (Ani and Agu, 2022). Therefore, the ANFIS algorithm uses an input-output correlation to predict the experimental data's result by combining fuzzy reasoning with a multi-layered neural network (Dolatabadi et al., 2020). This ANFIS model combination strategy produces a strong prediction capacity (Ani and Agu, 2022). When comparing the ANFIS to the ANN model, they both have numerical effectiveness and concurrent operation of the processes, which is the key factor for their broad acceptance (Ani and Agu, 2022). Fig. 6 shows the ANFIS flow diagram for generating a prediction model.

For the ANFIS to build a model, the fuzzy set and membership functions for each input variable need to be defined, which fuzzifies the input data. The rules then need to be created that describe the connection between the input variables and the output. Fuzzy inference will then be performed to determine the strength of each rule. Defuzzification then follows, whereby the fuzzy outputs from the rules are combined to obtain a crisp output. The parameters of the rules and membership functions are modified by employing the training data to improve the model's fit to the data. Evaluation matrices are also utilized to evaluate the model's performance, and validation and testing datasets will be employed to measure the model's performance. In both the ANN and ANFIS models, sensitivity analysis is usually done to confirm the significance of the proposed variables in the intended models.

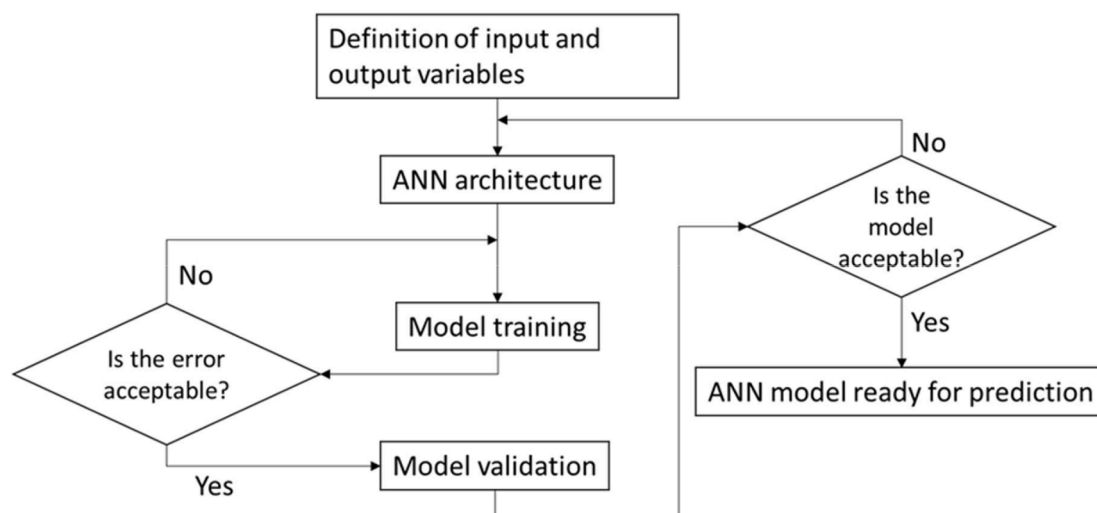


Fig. 5. ANN procedure flow diagram.

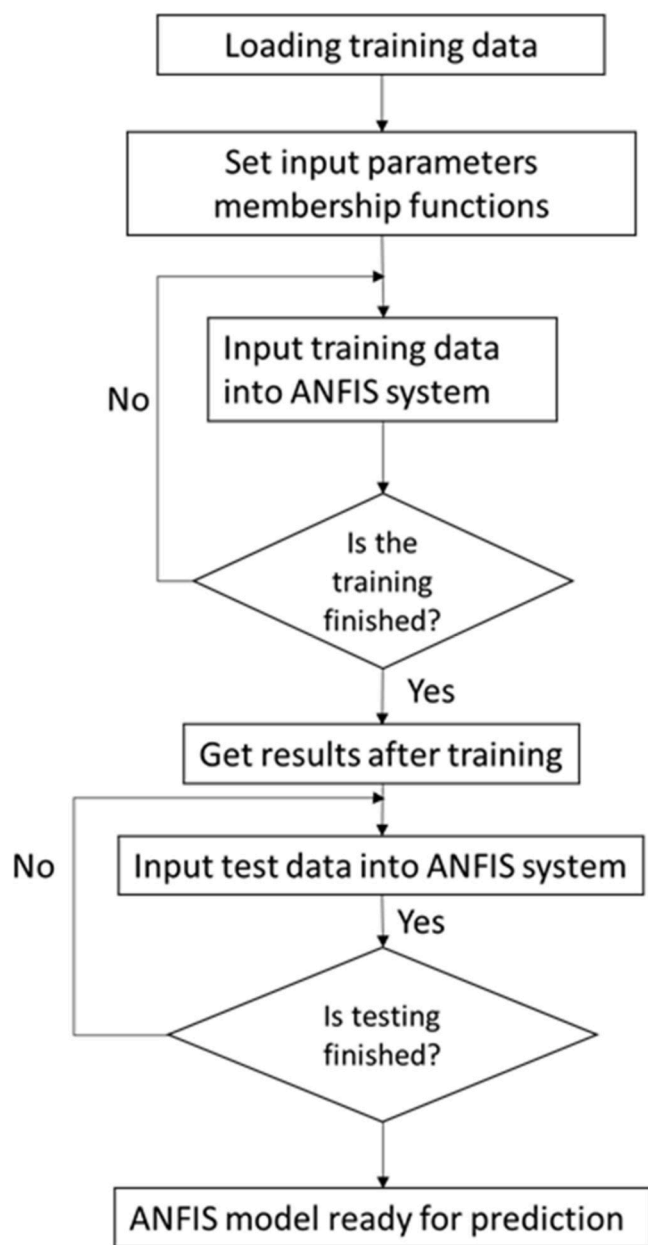


Fig. 6. ANFIS procedure flow diagram.

6.2. Advantages and limitations of ANN and anfis models

6.2.1. Advantages and limitations of ANN models

ANNs are powerful and versatile models that excel in capturing complex patterns in data. However, their success is contingent on circumstances of data quality, computational resources, and effective hyperparameter tuning. The interpretability challenge remains a significant limitation, especially in applications where model transparency is crucial. Table 2 highlights some of the benefits and drawbacks associated with the application and development of ANN models.

6.2.3. Advantages and limitations of anfis models

ANFIS models provide a hybrid method that blends fuzzy logic with neural network capabilities. They are remarkably suited for applications where interpretability and adaptability are essential. However, they also have limitations that should be considered in the modeling process. Table 3 gives an overview of the advantages and limitations of the ANFIS

Table 2

Advantages and limitations of ANN models.

Advantages	Limitations
Non-linearity and complex patterns: An ANN's ability to represent intricate, non-linear relationships in data makes it appropriate for applications where more conventional linear models might not be adequate (Khairunniza-Bejo et al., 2014).	Data dependency: ANNs often have a voracious appetite for data and may need a lot of labeled data to be trained. Inadequate data can lead to overfitting or poor generalization (Adadi, 2021).
Adaptability and learning: ANNs can adapt and learn from data. Through training, the network can adjust its weights and biases to improve its performance on a given task (Dongare et al., 2012).	Black box nature: The internal workings of complex neural networks can be difficult to interpret, leading to a black box problem. Grasping how the model arrives at specific predictions may be difficult (Dongare et al., 2012).
Parallel processing: ANNs can perform parallel processing, allowing them to handle multiple inputs simultaneously. This parallelism can lead to faster computation for certain tasks (Liu et al., 2016).	Computational intensity: Training deep neural networks, especially with large datasets, can be computationally intensive and may require specialized hardware (Prieto et al., 2016).
Feature learning: ANNs have the potential to replace manual feature engineering by automatically extracting relevant features from the input data (Khairunniza-Bejo et al., 2014).	Hyperparameter intensity: ANN models have numerous hyperparameters, and finding the optimal configuration can be challenging. Poorly chosen hyperparameters may result in suboptimal performance or training difficulties (Hossain and Timmer, 2021).
Generalization: Training ANNs can generalize well to new, unseen data, making them effective in making predictions (Alexandropoulos et al., 2019).	Vulnerability to noise: ANNs can be sensitive to noisy data, outliers, or irrelevant features. Robust preprocessing and data cleaning are crucial to mitigate these issues (Alexandropoulos et al., 2019).

models.

6.3. Application of ANN and anfis models in predicting and modeling emerging contaminants removal

Conventional wastewater treatment methods depend on the complex process, design, operational parameters, and mathematical calculations (Malviya and Jaspal, 2021). These are subject to numerous limitations, including financial, social, legal, political, and technological (Malviya and Jaspal, 2021). Prior techniques for statistical and multivariate data analysis were employed to assess the efficacy of pollutant removal and to estimate uncertainty (You et al., 2017). However, AI technologies like ANNs and ANFIS provide higher accuracy in the prediction of regression coefficients and relatively low average error without requiring intricate mathematical calculations or a thorough comprehension of the relationships between the input and output variables (Malviya and Jaspal, 2021). ANNs and ANFIS can accurately simulate complicated and highly nonlinear phenomena, they are widely utilized in hydrologic engineering applications, such as groundwater simulation, river flow prediction, rainfall-runoff modeling, and water quality simulation (Khazaei Poul et al., 2019).

They have proved their competence in tackling difficult, interactive and dynamic wastewater treatment challenges (Malviya and Jaspal, 2021). The effluent quality treatment processes has been predicted effectively with these models. Thus, bringing about timely action to inhibit the decline in quality. They have also been employed in automated sampling to assist operators in recognizing trends and patterns so they can take prompt action to avert possible mishaps (Malviya and Jaspal, 2021). AI models have been used in wastewater treatment in some contexts. AI technologies have also been used in the design of treatment units, effluent quality estimation, operational parameter optimization, and water treatment performance prediction (Malviya and Jaspal, 2021). Furthermore, AI has been used to create sensors for key

Table 3
Advantages and limitations of ANFIS models.

Advantages	Limitations
<p>Non-linearity handling: ANFIS models can capture precisely non-linear relationships in data and are a good fit for complex systems where linear models might not be sufficient (Zaghloul et al., 2020).</p> <p>Fuzzy logic interpretability: Fuzzy logic enables the integration of linguistic variables with human-like reasoning, enhancing the interpretability of the model. This can be valuable in decision-making systems where transparency is important (Taherdoost, 2023).</p> <p>Adaptability: ANFIS models can adapt to changes in the underlying data patterns, making them robust in dynamic environments. The adaptive learning capability allows them to continuously improve as more data becomes available (Hakim and Razak, 2013).</p> <p>Hybrid approach: Combining neural networks and fuzzy logic allows ANFIS to leverage the learning abilities of neural networks while retaining the interpretability of fuzzy logic (Dolatabadi et al., 2020).</p> <p>Universal approximation property: Like neural networks, ANFIS models have the universal approximation property, which means they can approximate any continuous function with sufficient parameters (Chopra et al., 2021).</p>	<p>Data-intensive training: ANFIS models may need a lot of data to train, particularly in situations with intricate underlying relationships. Insufficient data could lead to overfitting or poor generalization (Talpur et al., 2022).</p> <p>Computational complexity: The training process of ANFIS involves multiple iterations, and the complexity rises with the number of rules and membership functions. This can make training time-consuming and resource-intensive (Talpur et al., 2022).</p> <p>Difficulty in rule-based design: Designing an appropriate rule base for the fuzzy system in ANFIS can be challenging. Determining the right number of rules and their structure requires domain expertise (Taherdoost, 2023).</p> <p>Limited expressiveness for some applications: while ANFIS models can approximate a wide range of functions, they may not always be the best choice for tasks requiring highly complex, non-uniform decision boundaries, where deep neural networks might excel (Prieto et al., 2016).</p> <p>Black-box nature of neural networks: The neural network in ANFIS introduces a level of black-box complexity, making it challenging to interpret the internal workings of the model. Especially when dealing with large and deep networks (Talpur et al., 2022).</p>

component estimation, micropollutant and other EC optimization, maintenance strategy prediction, and several other applications (Malviya and Jaspal, 2021).

6.3.1. Publication characteristics

Numerous studies have been conducted in recent years to create effective models that would aid in forecasting the removal of the various ECs present in wastewater using modeling and prediction techniques. As

illustrated in Fig. 7, there has been a notable global rise in academic publications addressing this application. Between 2000 and 2010, the number of studies remained minimal and sporadic, with annual outputs ranging from 1 to 15, indicating that machine learning was still in its infancy within the wastewater treatment domain. From 2011 to 2016, a modest but steady increase occurred, with publication counts fluctuating between 3 and 15 per year. A more pronounced growth emerged between 2017 and 2020, where the number of publications rose from 11 to 23, reflecting a growing awareness of machine learning's potential in environmental engineering. The period from 2021 to 2025 saw a dramatic surge, with annual publications peaking at 114 in 2024, underscoring the expanding interest and integration of artificial intelligence in industrial and environmental applications.

6.3.2. Country contributions

An analysis of global contributions to research on AI and hybrid techniques in wastewater treatment, represented by Fig. 8, reveals that China leads with the highest number of publications (126), followed by India (76) and the United States (52), indicating their prominent role in advancing intelligent environmental technologies. South Africa ranks 14th among the top 20 contributing countries, with 18 publications. This is a noteworthy achievement, especially considering its status as a developing nation. South Africa's inclusion highlights its growing academic and institutional commitment to leveraging artificial intelligence for sustainable water management. The country's research efforts reflect a strategic response to local water quality challenges and infrastructure limitations, positioning it as an emerging player in the global environmental technology landscape.

6.3.3. Keyword co-occurrence

Examples of the different studies that have made use of artificial intelligence in wastewater treatment for the removal of emerging contaminants, specifically those using ANN and ANFIS, are briefly discussed in this section. A study by Nnaji et al. (2023a) used ANFIS and RSM to model and predict the coagulation-flocculation parameters required for efficient color and chemical oxygen (COD) removal, as well as acceptable sludge production, using *Mucuna sloanei* at 298 K for dye wastewater treatment. The model performance was assessed using the R^2 and RMSE. For color removal, ANFIS achieved $R^2=0.9823$ and $RMSE=0.2599$, while RSM recorded $R^2=0.8616$ and $RMSE=21.403$. For COD removal, ANFIS yielded $R^2=0.9752$ and $RMSE=0.2009$, compared to RSM with $R^2=0.9741$ and $RMSE=0.8118$. regarding sludge volume index (SVI), ANFIS reported $R^2=0.9950$ and $RMSE=0.2341$, whereas

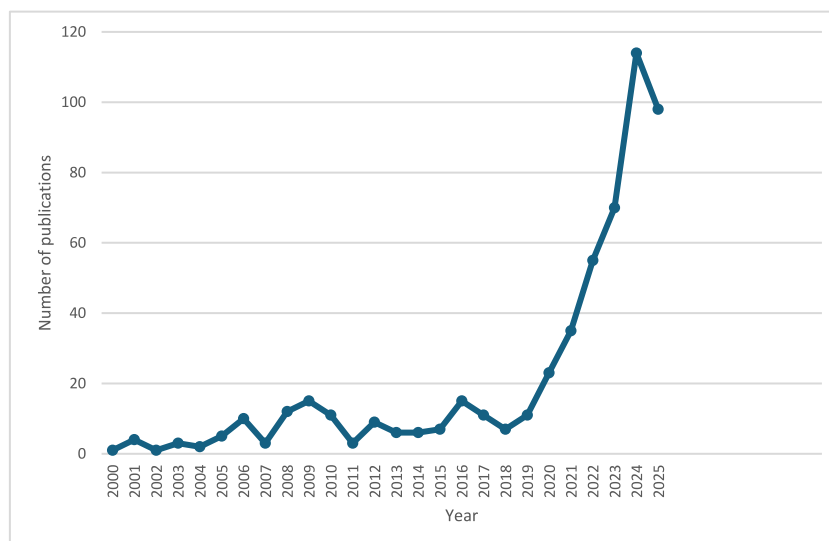


Fig. 7. Publication trend in 25 years (2000–2025).

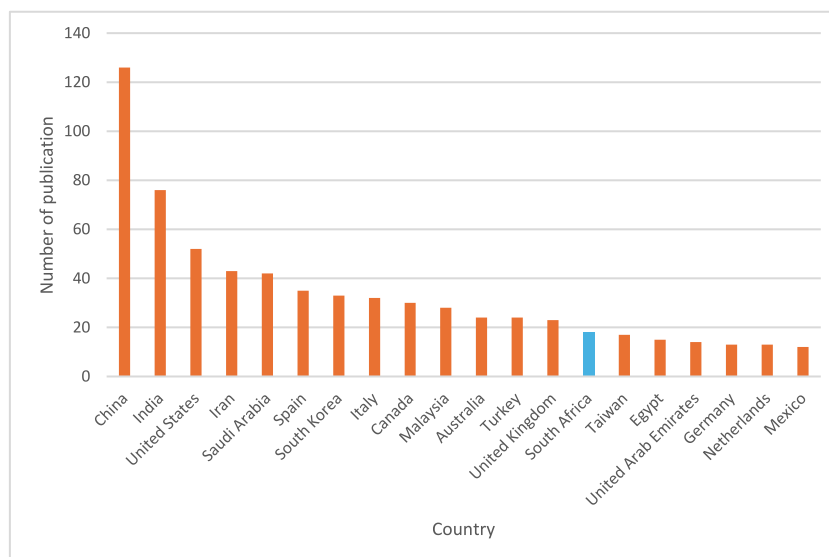


Fig. 8. Top 20 countries using AI/hybrid techniques in wastewater treatment (2000–2025).

RSM showed $R^2=0.9930$ and $RMSE=2.1436$. Despite the limited dataset, both models demonstrated strong predictive capability for color COD and SVI. However, ANFIS outperformed RSM due to its higher R^2 values and lower RMSE (Nnaji et al., 2023a). A similar study conducted by Nnaji et al. (2023b) assessed performance, sludge characteristics, and dual optimization in treating dye-contaminated wastewater using an oxidized starch-aluminum electrode system powered by direct current. Process optimization was carried out using RSM and ANN. RSM showed R^2 for color, COD and phosphate to be 0.9741, 0.9819 and 0.9311, respectively. ANN demonstrated superior predictive accuracy with $R^2 > 0.99$ for all responses, indicating its advantage over RSM. Overall, combining electrocoagulation with chemical coagulation proved highly effective for dye-laden wastewater treatment (Nnaji et al., 2023b).

Another study by Taheri et al. (2021) predicted transmembrane pressure (TMP), a critical factor in anaerobic membrane bioreactor-sequencing batch reactor (AnMBR-SBR) systems for bio-hydrogen production, using ANFIS and ANN models. The inputs in this study included COD that ranged from 0.5 to 8.0 g COD/L/d, effluent pH (3.6–6.9), mixed suspended solids (4.6–21.5 g/L) and volatile suspended solids (3.7–15.5 g/L). ANFIS, trained with hybrid algorithms and Gauss membership functions, achieved higher accuracy with the $R^2=0.93$ and $MSE=0.0073$ compared to ANN which had $R^2=0.88$, $MSE=0.00802$, which used a Levenberg-Marquardt algorithm with nine hidden neurons (Taheri et al., 2021).

Onukwuli et al. (2021) conducted a study that investigated the use of Luffa cylindrical seed (LCS) extracts, processed through different methods, as bio-coagulants for treating dye-contaminated wastewater simulated with Cibacron blue 3GA. The prediction models used in this study were RSM and ANN to estimate color/total suspended particle (CTSP) and COD removal based on dosage, pH, and stirring time. The model accuracy were assessed using R^2 and MSE. The results showed that the Sutherland extract achieved the best performance with ANN models demonstrating superior predictive capability with R^2 approximately 0.9999 compared to RSM. Overall, in this study, ANN was identified as the most effective tool for predicting CTSP and COD removal from dye-polluted wastewater (Onukwuli et al., 2021).

Another study by Asghari et al. (2022) applied black-box AI models, which included feed-forward neural network (FFNN), support vector regression (SVR), and ANFIS to predict effluent BOD and COD. Data from Tabriz WWTP collected daily from 2016 to 2018 were used to develop these models. For comparison, the linear autoregressive integrated moving average (ARIMA) model was also used (Asghari et al., 2022). The inputs included influent BOD, COD, TSS, pH at time t, and

previous BOD and COD effluent values at t-1, while outputs were the BOD and COD effluents at t. In this study, the SVR model performed best compared to the FFNN and ANFIS (Asghari et al., 2022). In the agricultural field Köksal et al. (2025) made use of a hybrid machine learning approach to forecast key effluent parameters in an advanced biological treatment plant and evaluated its reuse potential in irrigation. Three AI models were considered in this study, ANN, ANFIS and Fuzzy logic-Mamdani (FLM). These were applied to three years of inlet and outlet water quality data. Fuzzy logic assessed reuse stability, while ANFIS categorized quality parameters and ANN provided higher accuracy predictions with R^2 in the ranges of 74–99 %, and a low MSE. The results obtained from this study showed that 69–72 % of treated wastewater could be reused for irrigation, potentially covering 35 % of a 20,000 hectare area (Köksal et al., 2025). The integration of AI models has significantly enhanced prediction accuracy and interpretability, enabling optimization of wastewater treatment processes and promoting sustainable water reuse strategies in agriculture. Collectively, these studies demonstrate the transformative role of AI in advancing environmental engineering by improving the precision and efficiency of wastewater treatment modeling. Despite these advancements, limited research has focused on the removal of pharmaceutical contaminants and the application of AI models specifically designed to address this challenge, highlighting an important gap for future investigations.

7. Case studies on the application of ANN and ANFIS models in pharmaceutical removal

This section focuses on studies that utilised ANN and/or ANFIS to predict pharmaceutical removal and similar contaminants from wastewater. Research addressing other emerging contaminants was excluded from the detailed case studies, as the primary objective is to evaluate the effectiveness of ANN and ANFIS models specifically in modelling and predicting pharmaceutical removal processes from wastewater.

7.1. Optimizing antiretroviral drugs removal in tertiary wastewater using chlorination and AI-based modeling

Kang et al. (2024) conducted a study that applied RSM and ANN to model and optimize the degradation of Nevirapine and Efavirenz under varying chlorination conditions. Nevirapine and Efavirenz are antiretroviral drugs (ARVDs) which are ECs, and they are one of the most persistent antiretroviral drugs in wastewater effluents and surface waters (Adeola and Forbes, 2022). South Africa has reported one of the

high levels of these ARVDs. The influent and effluent concentrations of ARVDs in South Africa ranged from 670 to 34,000 ng/L and 540 to 34,000 ng/L respectively (Adeola and Forbes, 2022). In contrast, European levels are much lower, typically below detection limits to 32 ng/L influent and below detection to 22 ng/L in the effluent (Adeola et al., 2022). Traditional treatment plants often lack advanced monitoring systems to detect trace concentrations, which hinders the effective removal of these drugs (Kang et al., 2024). Thus this study aimed to model, predict and enhance the degradation of the pharmaceutical pollutants by evaluating different operational conditions in the chlorination process used for water treatment (Kang et al., 2024). The three independent variables used in this study were time, pH and temperature (Kang et al., 2024).

For the ANN model, this study used two ANN structures for its process, the feedforward Neural network (FFNN) and the recurrent neural network (RNN) (Kang et al., 2024). Both ANN models were trained using experimentally measured removal efficiency data and validated with an independent dataset to assess predictive performance. In this study, an ANN was developed to predict the removal efficiency of Nevirapine and Efavirenz from water. The model used Time, pH, and Temperature as input variables and removal efficiency as the output. Its primary goal was to capture the nonlinear relationships between these operational parameters and the degradation of the pharmaceuticals. Training involved adjusting network weights and biases to minimize the error between predicted and actual removal efficiencies (Kang et al., 2024). The ANN developed consisted of two hidden layers, utilizing Tangsigmoid and Logsigmoid activation functions, with up to five neurons in each layer. Model performance for predicting Nevirapine and Efavirenz removal was evaluated using three metrics, R^2 , MSE and mean absolute error (MAE) (Kang et al., 2024).

Both RSM and ANN models demonstrated strong performance in predicting the removal efficiency of Nevirapine and Efavirenz. However, ANN models outperformed RSM, especially for long treatment durations. For ANN, the R^2 was 0.9986 for Nevirapine and 0.9973 for Efavirenz, and the MSE for Nevirapine and Efavirenz were 9.25×10^{-5} and 7.62×10^{-57} , respectively. For the RSM the highest R^2 obtained for Nevirapine was 0.803, and that of Efavirenz was 0.776, this shows that the ANN model provided more accuracy in this study (Kang et al., 2024).

7.2. Modeling and optimization of psychoactive pharmaceutical caffeine removal by the electrochemical oxidation process

Another case study by Shirkoohi et al. (2022), centered on modeling and optimizing the electrochemical oxidation (EO) process for eliminating caffeine from psychotropic pharmaceuticals in synthetic solutions and urban wastewater effluent. The response surface methodology (RSM) and ANFIS-based central composite design (CCD) were employed in the study. The impact of independent variables such as anode type, starting caffeine concentration, current intensity, and electrolysis time was investigated. The emerging contaminant under investigation is pharmaceutical caffeine. Caffeine is a psychoactive alkaloid molecule belonging to the methylxanthine family that is extensively and lawfully used in meals, beverages, personal care items, and medications (Shirkoohi et al., 2022). While modest daily intakes of caffeine are thought to be harmless, high quantities of caffeine can aggravate underlying mental health conditions (Wikoff et al., 2017). Wastewater treatment plants in different parts of the globe are exposed to a detectable level of caffeine, primarily via excretory residues from caffeine consumption, the discarding of unused caffeinated drinks, pharmaceutical items, production wastes, and hospital wastes (Li et al., 2020). There has been evidence of caffeine found in the influent and effluent of WWTPs at varying concentrations (ng/L to mg/L) (Tawfik et al., 2024). Caffeine has a stated half-life of 100–240 days and is highly soluble in water (37.5 ± 1.0 g/L), making it incredibly stable once discharged into the aquatic media (Shirkoohi et al., 2022). The urban wastewater

effluent utilized in the study was sampled from Beauport, Quebec City, Canada, especially from the Quebec urban community (CUQ) WWTP (Shirkoohi et al., 2022).

Employing the investigational data gathered following DoE, the ANFIS models for this work were created in MATLAB R2019a. The removal efficiency and energy consumption were calculated using a single model with four inputs and one output for each response. The conduct of the CCD and ANFIS models was measured using R^2 , RMSE, and mean absolute percentage error (MAPE). The error function applied to train the ANFIS models was RMSE. The best conditions for energy consumption and caffeine elimination efficiency were determined by employing a CCD approach based on RSM to create a mathematical model for the prediction of the behavior of the electrochemical process (Shirkoohi et al., 2022). Training, validation, and testing sets of 40 tests each for energy consumption and caffeine removal efficiency from the CCD were used to generate the experimental data for the ANFIS models. 12.5 % of the data set was applied for validation to reduce overfitting and enhance the generalization performance of the trained model, and 75 % of the data set was used to train the ANFIS. The optimal model was then used on the remaining 12.5 % of the test data set to evaluate the ANFIS model's performance on the unseen data (Shirkoohi et al., 2022). ANFIS models were developed using the Fuzzy C-Means (FCM) clustering approach with the CCD dataset. By establishing a comparatively small number of rules, FCM combined with ANFIS helps to minimize the overfitting problem and keeps the model from becoming overly complex (Shirkoohi et al., 2022).

The FCM clustering approach was utilized to find the fuzzy membership functions and fuzzy rule base for the ANFIS model by dividing the input data into discrete clusters. The two models perform better overall for elimination efficiency and energy consumption for training samples as the number of clusters increases, as indicated by lower RMSE values, but worse for validation and test sets, as indicated by larger RMSE values. Both models reach a minimal value for the training RMSE when the clusters are set to four or higher. However, even though the models have likely learned the training set and noise, their capacity to generalize to new data has decreased, as indicated by the fact that the RMSE increases for the test and validation sets. Therefore, for energy consumption and caffeine elimination efficiency, the number of clusters was fixed to two (Shirkoohi et al., 2022). It can be seen that both the ANFIS and the CCD models accurately predicted the behavior of the electrochemical system when comparing the models for energy consumption and caffeine elimination. However, the ANFIS models did significantly better. The results indicate that the ANFIS models had computed R^2 values of 0.993 and 0.976 for energy consumption and caffeine elimination efficiency, respectively, whereas the CCD models' R^2 values were 0.986 and 0.939 for these two parameters (Shirkoohi et al., 2022). Additionally, ANFIS models displayed lesser deviations than CCD models, demonstrating their superior match to experimental data—particularly in the context of energy consumption.

7.3. The application of kinetics and ANFIS modeling for sustainable removal of diclofenac sodium

Another case study that was considered was the work by Sharma et al. (2023) which focused on the modeling and forecast of diclofenac sodium (DFS) removal from water using nitrogen-doped graphene nanosheets (NGS). DFS is a non-steroidal anti-inflammatory drug (NSAID) that is frequently used for both people and animals to treat rheumatoid arthritis, pain, inflammation, and dysmenorrhea (De Franco et al., 2018). It is considered to be the 12th best-selling drug according to global statistics, with an annual consumption of 1443 ± 58 tons (Lara-Pérez et al., 2020). As a result, DFS is now widely present in an array of water matrices due to its ubiquitous usage. Furthermore, because of its high solubility in water, removing DFS from water during conventional wastewater treatment is challenging. As a result, insufficient DFS removal in WWTPs leads to DFS presence in surface and even

drinking water. This raises dangerous worries for both aquatic and terrestrial species (Sharma et al., 2023).

This study used 320 data sets in MATLAB R2020a to train and evaluate the ANFIS model to determine the effects of pH, DFS concentration, contact time, stirring rate, and adsorbent dosage on the removal of DFS (Sharma et al., 2023). The five input variables employed to train the model were initial concentration, contact time, pH, dosage, agitation rate, and one output variable, adsorption percentage. ANFIS used the grid partition technique and adhered to the Sugeno-fuzzy model. The ability of the ANFIS to precisely forecast the adsorption of DFS from water by NGS was validated using R^2 , MSE, RMSE, and the sum of squares error. For DFS, during the initial training process, the error tolerance was set at 0 and 1000 epoch iterations. The training of the ANFIS model terminated after 181 epochs with an error magnitude of 0.0068, demonstrating the model's high accuracy in predicting pharmaceutical drug adsorption.

The results in this study confirm the applied training process was not over-fitted, as shown by the MSE, and the R^2 values, which are closer to 1, indicate genuine outputs. With suitable SSE <0.35, MSE <0.0018, RMSE <0.046, and higher R^2 values over 0.94, ANFIS presented superior results (Sharma et al., 2023). The reliability of the findings from the test was premised on the reduced values of MSE, SSE, and RMSE. It could be concluded that the removal efficiency of DFS adsorption using NGS could be well predicted using ANFIS (Sharma et al., 2023).

7.4. The use of computational and statistical models for optimizing key parameters on the electrochemical removal of cephalixin

One of the case studies was a study that was done by Arab et al. (2022) to enhance the effects of significant factors on the electrochemical elimination of antibiotic cephalixin. The approach focused on utilizing computational and statistical models to represent the antibiotics found in water. The experimental training data was forecasted in this study using ANN and ANFIS techniques, and the response surface methodology-central composite design (RSM-CCD) was used to examine the relationship between the variables of interest (Arab et al., 2022). The emerging contaminants under investigation are antibiotics (cephalexin antibiotics) in this study. One of the cephalosporin antibiotics with antibacterial qualities is cephalixin (CEX), which is utilized to remedy a range of ailments, including infectious diseases, brought on by gram-positive and gram-negative organisms (Arab et al., 2022). Therefore the consumption of CEX is relatively high and thus results in a high presence of CEX in effluents (Nazari et al., 2016). The ongoing introduction of CEX into the environment and water supplies will cause concerns for humans and the environment. The ineffectiveness of the wastewater treatment approaches for the elimination of such micropollutants has resulted in the investigation of different methods including photocatalytic decomposition, advanced oxidation, nanofiltration, adsorption, biofilms and as in this study electrocoagulation (Nazari et al., 2016). The study site for this research was Merck, Darmstadt, Germany.

The experiments were designed and optimized using the CCD response surface model. Concerning the ANN and ANFIS modeling approach, the ANN study used AI software (MATLAB 13a). The Levenberg Marquardt training technique and a sigmoid transfer (TANSIG) function were utilized to modify the ANN network. Eighty wastewater treatment trials with CEX were used to develop the ANN architecture. These trials were randomly assigned to subsections. 70 % of the trials were used for training, 15 % for validation, and the other 15 % for testing (Nazari et al., 2016). The input variables pH, electrolysis time, electrode type, and initial CEX concentration determined the number of input neurons. The elimination efficiency attained during EC treatment of the aqueous solution was the output variable (Nazari et al., 2016). The number of hidden layers and neurons within these layers were identified via trial and error. The ideal number of hidden nodes was determined using several nodes. Statistical analysis was performed utilizing the

correctness of the resulting models. For the ANFIS modeling, MATLAB 13b software was employed to examine and predict the electrocoagulation procedure for CEX removal. First, functions were used to create fuzzy clusters from the input values. The membership was then multiplied to determine the weights. Following the evaluation of each rule's normalized values, the weight values of these rules were calculated in each layer node (Nazari et al., 2016).

Using the Garson approach, a sensitivity analysis of ANN modeling was conducted to determine the relative importance of the influencing factor on the CEX removal process. The Levenberg-Marquardt (Trainlm) algorithm was employed to train the neural network since it was suitable for tiny and medium-sized data sets. Although having a small data set had drawbacks, Trainlm allowed the models to produce more accurate predictions. The validation set was used in this study to examine the network convergence to guarantee adequate generalization in the model and prevent overfitting, a common issue with AI models. Lastly, the prediction results on the test sets were displayed. The test sets were also utilized as a stand-in for hidden data. The results demonstrated that while employing 11 neurons with one hidden layer to forecast the elimination rate established based on the highest coefficient R^2 and the least MSE, using 13 neurons with two hidden layers proved to have the highest performance. Although there is not much difference between these two ideal conditions, using a single hidden layer is advisable due to the higher R^2 and MSE values. To limit the model's potential for greater generalization, 11 neurons from the hidden layer were chosen for the final version. The Pareto analysis was used to evaluate the sensitivity analysis of discrete parameters and the effects of their iterations, the Garson technique, and dual interaction for ANFIS, ANN, and RSM, respectively. The study's findings showed that while RSM, ANN, and ANFIS could all accurately predict the experimental results, the ANFIS model performed the best, with an R^2 of 0.9921, indicating that it could best predict the removal of CEX by the electrocoagulation technique (Nazari et al., 2016).

7.5. Experimental investigation and modeling for the adsorption of tetracycline antibiotic onto modified zeolite

This case study focused on the elimination of tetracycline (TC) by the adsorption technique and prediction of removal efficiency using the ANN and ANFIS models (Dolatabadi et al., 2020). R^2 , MAPE, and MSE were utilized to evaluate the predictive capacity of the models. Because of their excellent quality and affordable price, TC is a commonly used antibiotic for human treatment, animal disease prevention, and agricultural feed applications (Xu et al., 2021). They are obtained from different streptomyces species and a total of 20 compounds are introduced in the market as antibiotics (Granados-Chinchilla and Rodríguez, 2017). TC is regularly found in potable water, surface and groundwater, wastewater, and other environmental sources. This is because barely a slight portion of TC can be absorbed in the body, and up to 75 % of TC is typically excreted in its active form (Xu et al., 2021).

MATLAB (version 2014b) was used to computer code the necessary computations for the ANN model. 30 experimental data were used from this, and data sets were selected randomly, 74 % of the data sets were used for the training phase while 26 % was used for the validation. There was no testing phase in this study. Analysis of the data was carried out using Microsoft Office 2010 software, and trial and error and experience led to the optimum network design (Dolatabadi et al., 2020). The initial concentration of TC, pH, adsorbent dosage, and reaction time were the four input variables that were used, while the removal efficiency of TC was the outcome variable (Dolatabadi et al., 2020). The hidden layer, where a neuron with six distinct states was chosen to serve as the starting point for the modeling process. The state of each correlation coefficient for training, validation, and total data was determined; the correlation coefficient with the highest value was applied. The software was designed to allow for the exploration of every alternative configuration for the number of layers, neurons per layer, various transfer

functions, and algorithms once the training and validation stages were finished. Two Sugeno models with automatic ANFIS data extraction (GENFIS2) were utilized for the ANFIS model (Dolatabadi et al., 2020). The MATLAB program was used to create comparisons. The outcomes demonstrated that while both models can predict TC removal accurately, ANFIS predicts TC more precisely than the ANN model.

7.6. Adsorption of diclofenac and losartan using green-functionalized carbon nanotubes and machine learning modeling

Another study by Costa et al. (2024) explored the adsorption of diclofenac and losartan using green-functionalized multi-walled carbon nanotubes (CNTs) with iron nanoparticles. The research involved characterization of the adsorbent and analyzing surface interactions before and after adsorption using several characterization methods. The study also involved equilibrium studies at four temperatures (25–55 °C) to determine isothermal and thermodynamic behaviour (Costa et al., 2024). Furthermore, the modeling of adsorption was done using traditional isotherm models (Langmuir, Freundlich, Sips) and ML techniques, ANN and ANFIS. The best performing traditional and AI models were then compared to identify the most accurate approach.

This study applied AI to non-linear modeling of adsorption data using two network types, ANN and ANFIS. Both models were developed and implemented in MATLAB ®R2018a (Costa et al., 2024). Both networks used the same dataset derived from experimental equilibrium points for diclofenac and losartan adsorption on green CNTs. Inputs included temperature (25–55 °C), adsorbate type, and initial concentration. The output variable was the equilibrium adsorption capacity. In total, 96 experimental data points were used, and all values were normalized to a 0.1–0.9 range to maintain dataset consistency (Costa et al., 2024)

For the ANN, a feedforward neural network was developed, and two training algorithms were tested, Levenberg-Marquardt (LM) and Bayesian Regularization (BR). LM is an iterative method for minimizing the sum of squared errors; thus, it requires separate datasets for training, validation, and testing, which were split in a 70:15:15 ratio. In contrast, BR applies Bayesian inference to regularize the model and locate the global minimum without needing a validation set, so the data were divided into 85 % for training and 15 % for testing (Costa et al., 2024). Two activation functions were tested for the hidden layers, the hyperbolic tangent sigmoid (tansig) and the logarithmic sigmoid (logsig). The ANFIS models in this study were configured using Grid Partition clustering, two or three membership functions (MFs) per input variable, and Gaussian membership functions (gaussmf) for all inputs. The output membership functions were set as either constant or linear, optimization methods used either backpropagation and least-squares estimation and defuzzification was done via the weighted average method. Thus, in total, eight ANFIS network configurations were evaluated (Costa et al., 2024). To determine the optimal structural parameters for ANN and ANFIS models, performance was evaluated using R and MSE, aiming for R values close to 1 and MSE values near 0. Additionally, the mean relative deviation (MRD) was calculated to compare the best ANN and ANFIS models, with lower MRD values indicating better accuracy (Costa et al., 2024).

The results obtained proved that all models are effective in predicting adsorption performance. However, ANN outperformed ANFIS, achieving a highly accurate $R^2=0.9996$, $MSE=1.34 \times 10^{-5}$ and $MRD=1.91\%$, compared to ANFIS which had $R^2=0.9994$, $MSE=1.81 \times 10^{-5}$ and $MRD=4.68\%$. Furthermore, ANN significantly outperformed the traditional isotherm models such as Langmuir, which has $R^2=0.9650$, $MRD=36.04\%$ and Sips that had an $R^2=0.9602$ and $MRD=63.17\%$ (Costa et al., 2024). This outperformance confirms the effectiveness of machine learning for non-linear adsorption processes.

7.7. Comparison of ANN and ANFIS models for emerging contaminants removal prediction and modeling

The different case studies that were considered made use of different statistical evaluation metrics, such as MSE, R^2 , RMSE, MAPE, etc., to evaluate the performance of each model. However, for the sake of better comparison, the R^2 will be used in this study as the main comparison factor of the performance of the models in the selected studies, as shown in Table 4.

From Table 4, it can be noted that across most studies, AI models achieved higher R^2 and lower error metrics (RMSE/MAE/MSE/MRD) than classical statistical or isotherm models, indicating superior fit to nonlinear adsorption or removal behavior. Furthermore, ANFIS often provides higher R^2 and lower error metrics compared to ANN when they are both used in a study. However, there is an exception in the study by Costa et al. (2024) where ANN shows a small but consistent advantage over the ANFIS model.

Most of the case studies considered in this review use the ANFIS models. While comparing these different models in the same studies, it can be inferred that in all the studies, the ANFIS models provided a higher value of R^2 than ANN. This demonstrates that, among the various methods applied, ANFIS is the most effective modeling approach since it produces predictions of the contaminants' removal efficiency with a higher degree of accuracy. This is so because ANFIS integrates the fuzzy systems' reasoning abilities with the learning capabilities of ANNs (Dolatabadi et al., 2020). The least-squares approach and decent are used to create a hybrid learning algorithm for ANFIS. The hybrid approach has the advantage of converging much faster than the earliest basic back-propagation technique applied in neural networks, since it reduces the dimensions of the search space (Niknam Shahrak et al., 2019).

Even though ANFIS models are more accurate, their accuracy varies in each study, meaning that the different algorithms and modeling approaches that were used in this study had an impact on the performance of the models. The same is true about the ANN models that are presented by the different case studies. For the ANFIS models, the model that provided the highest R^2 value and in turn resulted in more accurate predictions was that of the pharmaceutical caffeine removal. The modeling approach that was used in this study included the use of 40 experimental data sets that were divided into 75 % training, 12.5 % validation, and 12.5 % testing, and the models were constructed using the FCM clustering method. ANFIS and FCM work together to acquire a manageably small set of rules in addition to the validation phase that minimizes the overfitting problem and keeps the model from becoming overly complex (Shirkoohi et al., 2022). The FCM clustering approach separates the input data into many clusters and finds the fuzzy membership functions and fuzzy rules based on the ANFIS model (Dolatabadi et al., 2020). One of the major characteristics of the FCM-ANFIS models is the number of clusters, identified as a hyperparameter for ANFIS model tuning and plays a crucial role in the network architecture and the trained model's simplicity or complexity. As a result, the ANFIS model demonstrated smaller deviations and a better ability to fit experimental data despite the small data set (Shirkoohi et al., 2022). ANFIS's main advantage is its capacity to improve fuzzy controllers with self-learning capabilities, hence minimizing mistakes. It is evident from comparing the ANN and ANFIS models in this study that the ANFIS model had slightly better precision than the ANN model.

7.8. Factors affecting the performance of the models

Various factors affect the model's performance, which could be seen from the different models in the case studies presented. The type of modeling approach has a substantial influence on the model performance, as it has already been established in the ANN and ANFIS models from the different results with ANFIS having the best output compared to the ANN model. ANN usually makes use of multilayer perceptron

Table 4
Comparing the effectiveness of ANFIS and ANN models in a few cases.

contaminant	Statistical models	ANN	ANFIS	References
Nevirapine and Efavirenz	$R^2=0.803$ Std.Dev=0.0546	$R^2=0.9986$ MAE=0.00339 MSE=0.0000925	–	(Kang et al., 2024)
Pharmaceutical caffeine	$R^2=0.986$ RMSE=3.778 MAPE=10.173	–	$R^2=0.993$ RMSE=2.694 MAPE=6.583	(Shirkoochi et al., 2022)
DFS	Langmuir: $R^2=0.99$ Freudlich: $R^2=0.96$	–	$R^2=0.940$ RMSE=0.046 MSE=0.0018	(Sharma et al., 2023)
CEX Tetracycline antibiotic	$R^2=0.9569$ –	$R^2=0.9816$ $R^2=0.9331$ RMSE=4.117 MAPE=0.046 MAE=2.832	$R^2=0.9921$ $R^2=0.9811$ RMSE=2.065 MAPE=0.013 MAE=0.759	(Arab et al., 2022) (Dolatabadi et al., 2020)
Diclofenac and losartan	Langmuir: $R^2=0.9749$ MRD=0.48 Sips: $R^2=0.9602$ MRD=0.63	$R^2=0.9996$ MSE=0.0000134 MRD=0.0191	$R^2=0.9994$ MSE=0.0000181 MRD=0.0468	(Costa et al., 2024)

(MLP) which is the most common neural network in problems of regression type (Park and Lek, 2016). The input, output, and hidden layers are all included. Based on trial and error, the optimal number of hidden layers and hidden units inside each layer is chosen. The hidden units are dependent upon the type of neural network being utilized (Park and Lek, 2016). While the determination of the hidden layer in ANN models is greatly determined using trial and error the ANFIS model provides a better approach. ANFIS's goal is to identify a mapping that accurately connects the input and target values (Roy et al., 2021). Since every fuzzy rule explains a system of local behavior, the fuzzy inference system is a knowledge representation. The type of hybrid or algorithm used significantly impacts the performance of the model. Various algorithms might be employed in the model according to their distinct features. Because the Levenberg-Marquardt (Trainlm) method may be used for small and medium-sized networks, for instance, it is used to train neural networks. As a result, even with tiny data sets, the algorithm selection can result in higher accuracy (Mahmoud et al., 2021). The training, validation, and testing phases and the amount of trial and error that may be done to modify the model all have an impact on how well the model functions. The training stage is crucial for creating an effective model with experimental data. Thus, it is essential to use a higher percentage of the data set for the training session so that the model can get different kinds of data to improve the outcomes during the training session. The validation data set is crucial to the model's functionality since it reduces overfitting and enhances the trained model's capacity for generalization (Malviya and Jaspal, 2021). The testing phase serves as a stand-in for hidden data, which is used to test and validate the model. All these steps are crucial in developing a model with high prediction performance. Additionally, it is crucial to carry out a sensitivity analysis, a method that finds out whether modifications to the input parameters have an impact on the model's output (Nazari et al., 2016). This will give feedback regarding which input parameters are most important, and by eliminating the ones that are not, the input space will be smaller, which will lower the model's complexity and the amount of time needed to train it. The sensitivity analysis results affect performance since removing one or more unnecessary input factors from the database can lead to better analyses with higher levels of performance prediction (Nazari et al., 2016).

7.9. Recommendations for choosing the appropriate modeling technique for specific situations

It is recommended that the models be used based on data availability and quality. For instance, if there is a large dataset with well-defined

input-output relationships and high-quality data, an ANN can be a suitable choice. This is because ANN models are capable of handling complex nonlinear relationships and can learn patterns and correlations from data effectively. However, if the dataset is limited, noisy, or contains uncertainties, ANFIS can be advantageous. This is because ANFIS models combine the capabilities of fuzzy logic and neural networks, which allows them to handle fuzzy and uncertain data through linguistic rules and fuzzy inference systems.

7.10. Emerging trends and new approaches in predicting and modeling pharmaceutical removal

The use of ANN and ANFIS models, which are AI models, is one of the emerging trends in modeling and predicting pharmaceutical removal. The use of statistical models is constantly being replaced by AI models, which have proven to provide more accurate predictions while also requiring fewer calculations, which can be tedious and time-consuming. From the case studies assessed in this review, it can be inferred that the current trends in predicting and modeling emerging contaminant removal make use of both statistical and AI models. For instance, in a study performed for the removal of CEX, both the RSM-CCD and ANN and ANFIS were used (Arab et al., 2022). The information obtained from the RSM-CCD was used to generate the datasets used for the ANFIS model. Similarly, the study by Costa et al. (2024) both traditional models and AI models to identify the most suitable modeling for the specific data of the study. This shows how the modeling approach includes the use of both statistical and AI models to attain higher prediction with the use of AI models.

8. Challenges and future directions

8.1. Challenges and limitations of the current modeling techniques

The current modeling techniques provide good predictions and performance based on how they have been developed. Both ANN and ANFIS models can provide significant prediction results in the removal of pharmaceuticals. However, most of the models were designed at an experimental scale rather than from a large-scale data set, therefore, the limitation provided by these models is that the level of data used is small and thus the performance attained may differ when data sets from wastewater treatment works are used. The use of small data sets can account for the limited availability of data for the removal efficiency of pharmaceuticals. The limited data raises a challenge as the ANN and ANFIS models require large and representative datasets for training,

validation, and testing. This challenge thus affects the results as the training phase is not done accurately due to limited datasets. The limited experimental data can also lead to poor validation and thus the developed model results in uncertainties and then becomes less reliable and applicable. Another challenge that is presented by these modeling techniques is that the ANN and ANFIS models can be complex and computationally intensive. The increase in the complexity of the model results in a decrease in the interpretability of the results; thus, it is difficult to interpret the internal mechanisms and decision-making processes of these models (Talpur et al., 2022). This challenge is greatly encountered with ANNs as they are from a class of “black box” models, whereby the information about the physical parameters of the process is not required (Talpur et al., 2022). The other challenge that can be faced is that of overfitting. When models are overfitted to the training data, they may perform poorly on new data, thus leading to limited applicability in real-world scenarios (Alexandropoulos et al., 2019).

8.2. Opportunities for future research and development

There are great prospects for future research and development in the prediction and modeling of the efficiency of different pharmaceuticals affecting water resources. There are a lot of pharmaceuticals that have been identified in recent decades; however, there are fewer prediction models available that can accurately help in determining their removal in the urban water cycle. Therefore, for future research and development, specific ANN and ANFIS models that deal with the removal of pharmaceuticals that are greatly impactful, like antibiotics, can be designed and many others for the prediction removal of these pharmaceuticals. For more precision accuracy, ANN and ANFIS models can be used simultaneously to provide two separate models that can be used co-currently. The ANN model can be used to develop a model that can later be updated and improved to an ANFIS model using the proper and necessary algorithms.

8.3. Prospects for the application of AI techniques in pharmaceutical removal prediction and modeling in the future

The possibilities for utilizing AI methods in EC removal and prediction are promising. They offer opportunities to enhance treatment efficiency through their prediction of removal efficiency. With AI assisting in predicting removal efficiencies, treatment processes can be optimized. Machine learning algorithms can analyze large datasets generated from treatment processes and identify patterns and correlations between process variables and contaminant removal. This can lead to optimization of treatment processes, such as adjusting operating conditions, optimizing chemical dosage, or identifying new treatment approaches for specific contaminants that will effectively remove them. To demonstrate better possibilities for producing optimum operation, increased pollution removal, and minimized operating cost, particularly under complicated operational settings, more hybridization of individual AI models is needed. Also, the ability of AI technologies to forecast outcomes should be enhanced by varying significant parameters involved in the wastewater treatment process. This would enable operators to effectively handle unexpected changes in parameters and guarantee that wastewater discharge meets water quality standards (Zhao et al., 2020). Future studies should concentrate on improving the use of AI in wastewater treatment research and design. This will allow the wastewater treatment sector to integrate AI technologies further to achieve breakthroughs in the removal efficiency of emerging contaminants, ultimately improving global health and the environment.

9. Conclusion

The degradation of water quality due to new contaminants is one of the biggest issues of concern to public health and the environment in developed and developing nations. The important point is that

wastewater treatment systems cannot adequately remove the pharmaceuticals that were assessed in this research according to their type, source, and occurrence. Although ANN and ANFIS are the most often used models for pollutant removal prediction from wastewater, other AI techniques are also used. The various case studies examined for this study showed that the cardinal factors affecting the broad adoption of the ANFIS and ANN models are their comparable numerical efficiency and simultaneous operational processes. An advantage that sets ANN apart from other machine-learning techniques is its infinite input and output. The ANN could be used to model nonlinear systems and does not need previous design fitting functions, which makes it more advantageous. Nonetheless, it was observed that the ANFIS model in this study provided the best forecast for the cases examined. ANN and ANFIS models are generally employed to predict and model the removal of contaminants, which helps to provide better wastewater treatment solutions and, consequently, improves water quality to achieve sustainable development goals.

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Data availability

No data were used for the research described in the article.

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All authors consented to participate.

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CRediT authorship contribution statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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