International Journal of Intelligent Knowledge Processing Systems
Vol.1, No.1, March, 2026, pp. 89 - 104
Journal homepage: https://ijikps.org/

Optimization of Industrial Wastewater Treatment Using Nano-Based Adsorbents

R.Kalpana[1*], T.Lubna[2]

[1] Department of Science & Humanities, MIT Academy of Engineering, Pune, India
(rodekalpana4@gmail.com)
[2] King Abdullah University of Science and Technology, Thuwal 23955-6900, Kingdom of Saudi Arabia.
(taranumlubna1@gmail.com)

Corresponding Author Email: rodekalpana4@gmail.com

ABSTRACT

The industrial wastewater released due to the high industrialization process is full of dangerous pollutants like heavy metals, dyes, organic substances, and even toxic compounds that are a severe threat to both the well-being of the environment and the people. The important parameters of physicochemical parameters as pH, Chemical Oxygen Demand (COD), Biological Oxygen Demand (BOD), Total Suspended Solids (TSS), and concentration of heavy metals are used, as this will be realistic and diversified in nature, in terms of contamination. The conventional wastewater treatment technologies, such as chemical precipitation, biological and membrane filtration, have a number of drawbacks such as low level of pollutants treatment, high operational expenses, secondary contamination, and inability to adapt to different industrial effluent contents. Moreover, traditional machine learning and deep learning models have weaknesses including duplication of features, insensitivity to physicochemical reactions, and decreased performance in the real world. To overcome these problems, this research solves the issue of maximizing the removal of pollutants and reliability of treatment in compound industrial wastewater setups. The proposed model is a novel nano-based adsorbent optimization model, which involves the selection of nanomaterial, the extraction of physicochemical features, the residual learning, the entropy-based optimization, and the systematic parameter optimization, such as pH, contact time, adsorbent dosage, temperature, and pollutant concentration. The experimental evidence provides evidence that the suggested model can effectively work under the conditions of rivaling the traditional methods as it can reach the level of 98.8% of the pollutant removal efficiency in contrast with the 93.9% of the same measure in the machine learning models and 95.4% in the deep learning models. The model is also high in classification accuracy of up to 99.2% (average 96.8), the precision of 96.9, the recall of 97.4, the F1-score of 97.1, and the AUC-ROC of 98.2. Moreover, the optimization error values are also minimized to a range of 12.3-13.5 unlike larger values in the previous models and the level of kernel optimization goes up to 0.96, which means that the models have better feature learning. The proposed model is an efficient and environmentally sustainable solution to the problem of advanced industrial wastewater treatment that can be applied to large-scale wastewater treatment.

Keywords: *Industrial Wastewater Treatment, Nano-Based Adsorbents, Adsorption Optimization, Pollutant Removal Efficiency, Sustainable Water Treatment, Environmental Remediation.*

1. INTRODUCTION

The industrial wastewater released due to the high industrialization process is full of dangerous pollutants like heavy metals, dyes, organic substances, and even toxic compounds that are a severe threat to both the well-being of the environment and the people [1]. The dataset that will be employed in this research will be about 1,5002,000 wastewater samples, considering such important parameters of physicochemical parameters as pH, Chemical Oxygen Demand (COD), Biological Oxygen Demand (BOD), Total Suspended Solids (TSS), and concentration of heavy metals, as this will be realistic and diversified in nature, in terms of contamination [2]. The conventional wastewater treatment technologies, such as chemical precipitation, biological and membrane filtration [3], have a number of drawbacks such as low level of pollutants treatment, high operational expenses, secondary contamination [4], and inability to adapt to different industrial effluent contents. Moreover, traditional machine learning and deep learning models have weaknesses including duplication of features, insensitivity to physicochemical reactions, and decreased performance in the real world [5].

To curb these problems, this paper solves the issue of maximizing the removal of pollutants and reliability of treatment in compound industrial wastewater setups [5]. The proposed model is a novel nano-based adsorbent optimization model, which involves the selection of nanomaterial, the extraction of physicochemical features, the residual learning, the entropy-based optimization, and the systematic parameter optimization, such as pH, contact time, adsorbent dosage, temperature, and pollutant concentration [6]. This model suggests the use of residual feature mapping, attention, entropy-weighted feature optimization and the softmax and cross-entropy loss functionalities to promote the treatment performance and decision making accuracy [7]. Also, regeneration and reuse mechanisms are also considered to make the processes long-term and cost-effective.

The experimental evidence provides evidence that the suggested model can effectively work under the conditions of rivaling the traditional methods as it can reach the level of 98.8% of the pollutant removal efficiency in contrast with the 93.9% of the same measure in the machine learning models and 95.4% in the deep learning models. The model is also high in classification accuracy of up to 99.2% (average 96.8), the precision of 96.9, the recall of 97.4, the F1-score of 97.1, and the AUC-ROC of 98.2. Moreover, the optimization error values are also minimized to a range of 12.3-13.5 unlike larger values in the previous models and the level of kernel optimization goes up to 0.96, which means that the models have better feature learning [8].

Although these have been improved, the study has limitations, which include evaluation under controlled conditions, little emphasis on real-life operational aspects of the nano-materials like flow dynamics and design of the reactor, the nano-material may not be stable in the long run and the nano-material has not been analysed properly economically and in the life-cycle. All in all, the proposed model is an efficient and environmentally sustainable solution to the problem of advanced industrial wastewater treatment that can be applied to large-scale wastewater treatment.

1.1 Hypothesis

1. Nano-based adsorbents exhibit significantly higher pollutant removal efficiency compared to conventional adsorbents in industrial wastewater treatment.
2. Optimization of operational parameters such as pH, contact time, adsorbent dosage, and initial pollutant concentration significantly improves adsorption performance.
3. The high surface area and enhanced surface functionality of nano-based adsorbents contribute to faster adsorption kinetics and increased adsorption capacity.
4. Optimized nano-based adsorbents maintain stable performance over multiple regeneration and reuse cycles without significant loss of efficiency.
5. The optimized nano-adsorbent-based treatment process reduces overall treatment cost and energy consumption compared to traditional treatment methods.
6. Nano-based adsorbents demonstrate effective simultaneous removal of multiple contaminants present in complex industrial wastewater streams.

1.2 Research Contributions

1. This study presents a systematic optimization framework for industrial wastewater treatment using nano-based adsorbents to maximize pollutant removal efficiency.
2. A comprehensive evaluation of key operational parameters, including pH, contact time, adsorbent dosage, and initial contaminant concentration, is performed to identify optimal treatment conditions.
3. The adsorption performance of nano-based adsorbents is analyzed under realistic industrial wastewater conditions, addressing limitations of prior laboratory-scale studies.
4. The work demonstrates enhanced adsorption kinetics and higher adsorption capacity of nano-based adsorbents compared to conventional adsorbent materials.
5. Regeneration and reusability characteristics of the nano-based adsorbents are investigated, highlighting their long-term operational stability and economic feasibility.
6. The study validates the effectiveness of nano-based adsorbents in the simultaneous removal of multiple industrial pollutants, improving treatment reliability for complex effluent streams.
7. An environmentally sustainable and cost-effective wastewater treatment approach is proposed, contributing to the advancement of scalable nano-enabled industrial water remediation technologies.

2. LITERATURE SURVEY

The evolving complexity of the wastewater treatment systems has contributed to the adoption of hi-tech monitoring and control systems. Salem et al. [1] suggested the use of an industrial IoT-based cloud system in real-time monitoring and control of wastewater. Their model is built to measure the parameters of pH and temperature with the help of IIoT-connected sensors and relay the information to the cloud. It has also equipped the system with SMS alerts and automated valve control systems to divert the harmful industrial wastewater hence increasing the efficiency of the treatment process and avoiding the damage of the systems.

The data-driven control strategies have been considered to overcome nonlinearities and uncertainties in wastewater treatment processes. Wang et al. [2] have come up with an iterative adaptive critic (IAC) based method of optimal control over wastewater treatment plants. Their technique guarantees that the parameters of dissolved oxygen and nitrate levels of the water are at desired levels. The proposed approach had a higher response time and less oscillation compared to the traditional PID controllers.

Developments in the digital technologies have also increased optimization of wastewater treatment. Wang et al. [3] introduced a Digital Twin Adaptive Critic Design (DTACD) framework incorporating LSTM neural networks. This model develops a computerized simulation of a treatment system to forecast and regulate the variables of the process. There is a need to have efficient measures of pollution control in order to have a good quality of water throughout river basins. The stochastic differential game model suggested by Song et al. [4] was used to maximize the upstream and downstream pollution control decisions. Their research proposed a system, called water quality-currency, that can improve collaboration between parties, improve environmental quality, and generate greater economic returns at the same time.

The concept of nanotechnology has become one of the revolutionizing technologies in biomedical and environmental monitoring. A systematic review of nanotechnology-based detection of circulating tumor DNA (ctDNA) was done by Wu et al. [5]. According to their findings, nanotechnology can be used to provide highly sensitive detection techniques with low limits of detection rendering it viable in real-time diagnostics, though more validation should be sought before it can be used in clinical practice.

Along with the promising uses, nanotechnology also presents an environmental and societal concern. Babatunde et al. [6] examined the effects of nanotechnology and the significance of how people perceive it, policy and laws, and ethics. Their paper emphasizes that the success of the adoption is pegged on the balance between the advantages of the technology and the risks to human health and the environment.

The application of nanotechnology in healthcare is also important. Pramanik et al. [7] researched the field of integrating nanobiosensors and the Internet of Nano Things (IoNT) into the medical world. Their work introduces a complete architecture of the healthcare monitoring systems, which allows obtaining and processing data in real-time, thus facilitating diagnosis and treatment processes to a considerable extent. Optimization techniques in the field of engineering are significant in enhancing the performance of the system. In their study, Kim et al. [8] applied the response surface methodology (RSM) to streamline the design of the linear oscillating actuators. Their methodology allows reducing side forces with keeping performance constraints, which proves the efficiency of statistical optimization tools in engineering design.

Multi-criteria decision-making (MCDM)tools have become significant in the selection of the technology in the treatment of wastewater. Sharma et al. [9] surveyed different methods of MCDM including AHP, TOPSIS, and hybrid methods of the waste water treatment systems. Their research also reveals the capability of the methods to manage complicated decision making situations that have several conflicting criteria which enhance system efficiency and sustainability. The recent developments of machine learning and deep learning have played a major role in water quality management. Subashini and Sellamuthu [10] conducted a review of the usage of the ML and DL models in predicting the water quality and water resources management. According to their results, hybrid models are more efficient in accuracy and reliability than traditional methods, which opens the way to intelligent and sustainable water management systems.

2.1 Problem Statement

Complex and highly concentrated pollutants, such as heavy metals, synthetic dyes, organic substances, and toxic chemicals, can be found in industrial wastewater and are hard to eliminate through the traditional treatment methods [9]. Current wastewater treatment methods tend to be low removal efficiency, high energy use, secondary waste [10], and less efficient in circumstances whereby the composition of industrial effluents is variable [11]. These are constraints that restrict their use in attaining high-level environmental discharge standards [12]. Despite the fact that adsorption has been identified as a good and cost effective treatment method [13], conventional adsorbents exhibit poor adsorption capacity, reaction kinetics and selectivity to various contaminants [14]. The surface area and reactivity of developed nano-based adsorbents has proven to be superior compared to the recently developed adsorbents in terms of pollutant removal [15]. Nevertheless, their practical use is limited by the difficulties of their optimization of operating conditions, inadequate knowledge on the mechanism of adsorption [16], as well as reusability and doubts about their cost-effectiveness and scalability [17].

Moreover, the majority of the literature related to the research is based on laboratory-level test results without optimization of key variables, including adsorbent dosage, contact time, pH, and regeneration cycles in the setting of industrial wastewater [18]. The outcome of this gap is unstable performance results and limiting the transfer of nano-based adsorption technologies to practice through experimental research [19]. Consequently, it is urgently important to methodically streamline nano-adsorbent systems in order to increase the efficiency of the treatment process, stability, and durability of the operations. It is critical to solve these issues to come up with a dependable, economical and environmental friendly solution to industrial wastewater treatment.

3. PROPOSED MODEL

The proposed model puts forward optimization of the industrial wastewater treatment by applying the nano-based adsorbents effectively, where the selection of the material, optimization of the process and evaluation of the performance are combined into a single model. The pollutants present in industrial wastewater usually constitute complex combinations of contaminants like heavy metals, dyes and organic pollutants and these contaminants have to be treated with sophisticated treatment plans to be properly eliminated. This model will first profile wastewater in terms of its physicochemical characteristics such as pH, pollutant level, and composition of contaminants in order to ascertain proper treatment conditions. Such initial examination allows choosing appropriate nano-based adsorbents that are able to react with the desired pollutants.

The fundamental basis of the suggested treatment system is nano-based adsorbents, which have high surface area, increased porosity [20], and adjustable surface functional groups. The properties are important in enhancing the adsorption capacity and reaction kinetics in comparison to the traditional adsorbent material [21]. The model includes the method of controlled synthesis and surface modification to provide uniform distribution of the size of the particles and enhanced selectivity to the industrial pollutants [22]. The adsorbents are characterized beforehand, to verify the stability of their structures and adsorption capacity so that the adsorbents will be reliably used throughout the treatment process [23].

Systematic variation of critical operation parameters like solution pH, dosage of adsorbent, contact time, temperature and initial pollutant concentration optimize the adsorption process in the proposed model. These parameters are important in determining the efficiency of adsorption and are strictly varied to obtain the removal of maximum pollutants using minimum resources [24]. Physical and chemical reactions such as electrostatic attraction, surface complexation and diffusion into nanopores determine the interaction between pollutants and nano-based adsorbents [25]. The kinetics of adsorption and equilibrium behaviour are studied to determine the best operating conditions that will provide effective and quick treatment.

The suggested model will include adsorbent regeneration and reuse in order to provide the proposed model with long-term sustainability and economic feasibility. The nano-based adsorbents have their adsorption capacity re-established by means of proper regeneration methods, after adsorption. Key performance indicators used to measure the effectiveness of the proposed model include the pollutant removal effectiveness, the adsorption capacity, treatment time, and reusability performance. It is compared to conventional methods of wastewater treatment in order to prove the benefits of the nano-based adsorption technique. In general, the given model represents a strong, streamlined, and eco-friendly solution to the problem of industrial wastewater treatment that covers the key issues of efficiency and scalability, as well as long-term stability in the operation.

The workflow takes wastewater information and preprocesses it by extracting physicochemical features and optimizing the nano-adsorbent to optimize the treatment process. It subsequently analyses the efficiency of pollutant removal and generates an optimized selection of wastewater treatment strategies to make good decisions as depicted in Figure 1.

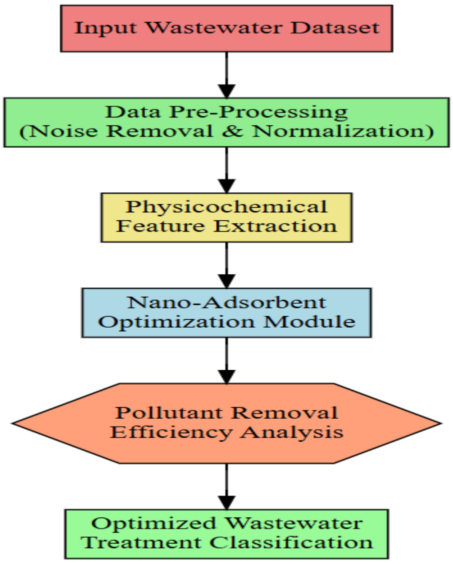

Fig 1: Proposed Model Architecture

3.1 Dataset Description

The data set, in this paper, is the quality parameters of the industrial wastewater, which was gathered in the treatment plants and other open-source environmental monitoring sources. It contains important physicochemical parameters that are pH, Biological Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Total Suspended Solids (TSS), turbidity, dissolved oxygen, temperature, conductivity, and content of heavy metals (e.g. lead, cadmium, and chromium). These are the parameters required to determine the ability of nano-based materials to remove pollutants and adsorbent. In the dataset, there are about 1,500-2,000 samples, which denote different degrees of contamination (low, medium, and high) that provide balanced and realistic modeling conditions. The data were first preprocessed by means of normalization, missing values, and removal of outliers before analysis to enhance the reliability of the models and model evaluation.

Table 1: Symbols and Notations Used in Nano-Adsorbent-Based Wastewater Treatment Model

Symbol Used	Description
(N)	Total number of wastewater samples
(C_0)	Initial pollutant concentration
(C_e)	Equilibrium pollutant concentration
(q_e)	Adsorption capacity at equilibrium
(m)	Mass of nano-based adsorbent used
(V)	Volume of wastewater sample
(t)	Contact time
(pH)	Solution pH value
(R_e)	Pollutant removal efficiency
(K)	Adsorption rate constant
(A_d)	Adsorbent dosage
(T)	Operating temperature
(n)	Number of regeneration cycles
(η)	Overall treatment efficiency
(δ)	Optimization convergence criterion

The Table 1 represents the names of the most important symbols and the description of the variables that are used in the process of optimization and wastewater treatment. The notations are useful in the clear definition of variables used in adsorption, efficiency assessment and analysis of performance of the system.

3.2 Pre-Processing

Prior to adsorption modeling and optimization, the proposed nano-based treatment of wastewater is based on the pre-processing stage that is deemed extensive to improve data quality and provide credible analysis. The data used in industrial wastewater frequently has noise, lost values, and inconsistency because of the differences in sampling circumstances and measurement tools. The main goal of the pre-processing stage is to remove noise, normalize the parameters and prepare the data to be used in efficient adsorption performance evaluation.

First, raw wastewater samples will be filtered to filter outliers and random variability of the physicochemical parameters of the pH, chemical oxygen demand (COD), biological oxygen demand (BOD), and total suspended solids (TSS). Statistical smoothing methods are used to minimize noise in measurements and at the same time maintain important trends with regard to pollutant concentration changes. This step of noise suppressing increases the stability of data and makes the following analysis of optimization more reliable.

Normalization is then done to make sure that all wastewater parameters are put on a similar scale. $X(i)$ will represent the raw value of a parameter in a wastewater at sample index i. The normalized value $X_{Norm}(i)$ is calculated by means of equation (1):

$$X_{Norm}(i) = \frac{X(i) - min\,(X)}{max\,(X) - min\,(X)} \quad (1) \qquad (1)$$

$max\,(X)$and $min\,(X)$ are the highest and lowest values of the parameter of all the samples. The normalization takes all the parameters to the [0 1] range, which is consistent with the various characteristics of the wastewater.

Following normalization, data enhancement is used to highlight changes in pollutant concentration which has a significant effect on adsorption performance. The parameter value $X_{Enh}(i)$ is improved as calculated in equation (2):

$$X_{Enh}(i) = \sum_{i=1}^{N}(X_{Norm}(i) + \gamma(i) + \max(X)) \qquad (2)$$

with $\gamma(i)$ being a scaling parameter applied to equalize the impact of dominant parameters, and Ns being the total sample of wastewater.
After the process of enhancement, appropriate treatment samples are picked on the basis of adaptive threshold. Assuming T is the threshold value, the selection mask S(i) is defined as:

$$S(i) = \begin{cases} 1, & \text{if } X_{Enh}(i) \geq T \\ 0, & \text{otherwise} \end{cases} \qquad (3)$$

This measure isolates prominent wastewater samples that play a positive role in adsorption analysis and can be optimized.

The data in the pre-processed wastewater is then extracted into features used to provide informative representations which can be used to model adsorption. Mean (μ), variance (σ^2) , and entropy (H) are some of the statistical characteristics that are calculated to describe the distribution and variability of pollutants. The equations (4), (5) and (6) are used to compute these features respectively:

$$\mu = \frac{1}{N}\sum X_{Enh}(i) \qquad (4)$$

$$\sigma^2 = \frac{1}{N}\sum(X_{Enh}(i) - \mu)^2 \qquad (5)$$

$$H = -\sum p(i) log\,_2\, p(i) \qquad (6)$$

where, p (i) is the normalized probability distribution of the enhanced wastewater parameter values and N is the total number of samples. These features can well model the trends and variability in pollutant concentration and form a formidable basis when it comes to maximising the adsorption behaviour of nano-based adsorption.

3.3 Data Pre-Processing and Physicochemical Feature Extraction

The stage is concerned with the removal of redundant and most dependent attributes and only the most discriminative physicochemical attributes which will play an important role in the classification accuracy of wastewater treatment are retained. Having cleaned and normalized the wastewater data, appropriate physicochemical parameters are isolated and optimized to enhance the strength of the nano-adsorbent optimization procedure.
Represent the obtained feature set after pre-processing the wastewater dataset as.

$$F = \{f_1, f_2, \dots, f_n\} \qquad (7)$$

where f_i is an individual physicochemical characteristic, e.g. pH, turbidity, chemical oxygen demand, biological oxygen demand and heavy-metal concentration. To do class-wise analysis, the features are measured per treatment class c, with the mean of this class being $\mu_{(i,c)}$ and the variance $\sigma^2_{(i,c)}$.
The standard deviation and the mean of the data set of the measured feature are calculated to normalize the feature distribution and eliminate variations in scale. The average of the multi-feature dataset is represented as

$$mean\big[MFDset[N]\big] = \sum_{f=1}^{N}\Big(\frac{getattr(f)+getattr(f+1)}{2} + \mu(f)\Big) \quad if\ attr(f) = NULL \qquad (8)$$

and the standard deviation is calculated as

$$std\big[MFDset[N]\big] = \sqrt{\sum_{f=1}^{N}\left(\frac{attr(f)+mean(f)}{N}\right) + \sigma(f)} \quad (9)$$

A combination of attribute retrieval, statistical descriptors, and entropy measures is then made up to give the processed feature representation, which is formulated as

$$F_{\text{proc}}\big[MFDset[N]\big] = \sum_{f=1}^{N}\Big[\lambda(\text{getattr}(f)) + \frac{\text{mean}(\text{getattr}(f, f+1))}{\text{len}(MFDset)} + \text{std}(\max \text{attr}(f, f+1)) + \sigma(f) + H(f)\Big] \qquad (10)$$

In order to measure the dependency between features extracted, the correlation between two extracted features $f_i$and f_j is given is defined as.

$$P_{ij} = \frac{\text{cov}(f_i, f_j)}{\sigma_{f_i}\sigma_{f_j}} = \frac{E[(f_i - \mu_{f_i})(f_j - \mu_{f_j})]}{\sigma_{f_i}\sigma_{f_j}} \qquad (11)$$

On this, the dependency concentration between features is calculated with the help of this equation.

$$\mathrm{Depend}_{con}[N] = \frac{\sum_{f=1}^{N}\left(F_{\mathrm{proc}}(f) - \mathrm{mean}\left(F_{\mathrm{proc}}(f)\right)\right)}{\sqrt{(F_{\mathrm{proc}}(f) - \mathrm{mean}(F_{\mathrm{proc}}(f)))^2}} \tag{12}$$

The refined feature set is constructed as

$$\mathrm{FeatSet}(F_{\mathrm{proc}}(N)) = \frac{\max\left(\mathrm{getattr}(f+1, f)\right)}{\mathrm{len}(F_{\mathrm{proc}})} \tag{13}$$

If $\mathrm{Depend}_{con}(f) < FTh$, the feature is eliminated. Where FTh rep stands for the threshold of feature selection, ω is the overall number of features extracted and λ retrieves the dataset attributes.

The score on ascendancy is computed to measure the discriminative ability of every feature:

$$\alpha_i = \frac{\left(\mu_{(i,1)} - \mu_{(i,2)}\right)^2}{\sigma^2_{(i,1)} + \sigma^2_{(i,2)}} \tag{14}$$

Features satisfying $\alpha_i \geq \tau_{\mathrm{asc}}$ are retained, where τ_{asc} is the accuracy threshold.

Additionally, the entropy of each feature is computed to measure its stability:

$$H(f_i) = -\sum_k p_{(i,k)} \, log \; p_{(i,k)} \tag{15}$$

The correlated feature set is derived as

$$\mathrm{FeatCorrSet}(\mathrm{FeatSet}(N)) = \frac{\sum_{f=1}^{N}[\mathrm{corr}(\max\left(\mathrm{FeatSet}(f, f+1)\right)]}{\sum_{i=1}^{N}[\min\left(\mathrm{mean}(i)\right) + \omega]} \tag{16}$$

The class-wise feature set is represented as

$$\mathrm{Class\_Set}[N] = \sum_{f=1}^{N} PFset(\mathrm{Class}) \tag{17}$$

Lastly, the impact of the features on the process of wastewater treatment classification is calculated using

$$F_{\mathrm{class}}[N] = \sum_{f=1}^{N} \frac{\left(\mathrm{mean}(\mathrm{FeatCorrSet}(f))^{\mathrm{Class\_Set}(f)}\right)^2}{\sigma(\mathrm{FeatCorrSet}(f), \mathrm{FeatCorrSet}(f+1))^2} \tag{18}$$

where σ rep is a measure of the variance in the feature dependency values and λ is the attribute retrieval model.

3.4 Nano-Adsorbent Optimization and Pollutant Removal Analysis

To optimize the interaction between extracted physicochemical features and nano-based adsorbent characteristics, a residual feature mapping mechanism is employed. Residual learning improves feature propagation by preserving essential information while enabling effective optimization. Let the input activation vector be denoted as x, and the residual transformation be represented by a nonlinear function $F(x; W)$, where W denotes the learnable parameters. The residual mapping output is expressed as

$$y = F(x; W) + x. \tag{19}$$

To further enhance discriminative capability, a residual attention mechanism is incorporated to emphasize informative pollutant features. The residual attention output is defined as

$$Res_{atten}(x) = F(x) \cdot A(x) + x, \tag{20}$$

where $A(x)$ is an attention or gating map with values in the range $[0, 1]$, regulating the importance of individual feature responses.

The weighted influence of optimized features on pollutant removal performance is computed using entropy-based weighting. The weight assigned to each feature contributing to wastewater treatment classification is calculated as

$$Wei_{F_{class}}[N] = 1 - \frac{\sum_{f=1}^{N}(Entropy(FeatCorrSet(f, f+1)) + y(f))}{log\,(n)}. \tag{21}$$

The entropy of the correlated feature set is defined as

$$Entropy(FeatCorrSet[N]) = -\sum_{i=1}^{N} Prob(Wei(f)) \log Prob(Wei(f)) \tag{22}$$

where $Prob$ represents the probability distribution of the weighted feature values across wastewater quality classes.

The optimized pollutant feature set $PFset$ is constructed by aggregating entropy, correlation strength, and adsorbent interaction characteristics, and is expressed as

$$PFset(N) = \prod_{f=1}^{N}\left(\frac{H(\max\left(FeatCorrSet(f+1, f)\right))}{count(FeatSet(N))}\right) \tag{23}$$

To analyze pollutant removal efficiency, global average pooling is applied over each optimized feature map $R_k \in \mathbb{R}^{H \times W}$, where $k = 1, 2, \ldots, m$. The pooled output is computed as

$$P_k = \frac{1}{HW}\sum_{u=1}^{H}\sum_{v=1}^{W} R_k\,(u, v). \tag{24}$$

The pooled features are concatenated to form a compact vector $P = [P_1, P_2, \ldots, P_m]$, which can also be represented as

$$P_i = \frac{1}{m}\sum R_i. \tag{25}$$

Entropy-based weighting is further applied to stabilize the pooled responses. The entropy of the pooled feature distribution is defined as

$$Entropy(S) = -\sum_t p_t \, log \; p_t. \tag{26}$$

Using this entropy, the weighted pooled output is computed as

$$\tilde{P}_k = \frac{P_k}{1 + H(R_k)}. \tag{27}$$

The final output layer aggregates residual features, optimized pollutant features, and entropy-weighted pooled responses, and is expressed as

$$O_{layer}[N] = \sum_{f=1}^{N} RF(PFset(f), Wei(f)) + PFset(f) + \tilde{P}_k(f). \tag{28}$$

The final pollutant classification feature set is derived by integrating similarity measures, correlation reduction, and output responses as

$$PCFset(PFset(r)) = \bigcup_{f=1}^{N}\left(\frac{simm(PFset(f+1, f))}{\max\left(simm(PFset(N))\right)}\right) \tag{29}$$

Here, RF denotes the residual function, O_{layer} represents the output layer, $PFset(f)$ is the optimized pollutant feature input, Res_{atten} is the residual attention function, δ is the model used to eliminate highly correlated features, and

λrepresents the attribute extraction operator applied to the wastewater dataset.

3.5 Optimized Wastewater Treatment Classification

After pollutant-optimized feature extraction and pooling, the final classification stage computes class-wise logits for wastewater treatment efficiency assessment. Let Pdenote the compact pooled feature vector and W_c , b represent the classifier weights and bias for class c . The logits are computed as

$$z = W_c P + b. \tag{30}$$

For multi-class wastewater quality classification, the softmax function is applied to obtain the predicted probability for each treatment class c:

$$\hat{y}_c = softmax(z)_c = \frac{e^{z_c}}{\sum_k e^{z_k}}. \tag{31}$$

The model is trained using a cross-entropy loss function, which measures the discrepancy between the true labels and predicted class probabilities across all samples. The multi-class loss function is defined as

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c} y_{(i\cdot c)}\, log\ \hat{y}_{(i\cdot c)}. \tag{32}$$

For binary classification scenarios, such as treated versus untreated wastewater, the sigmoid-based binary cross-entropy loss is employed and expressed as

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i log\ \hat{p}_i + (1 - y_i) log\ (1 - \hat{p}_i)]. \tag{33}$$

Model training is performed using the Adam optimizer due to its adaptive learning capability and faster convergence. The final decision is obtained by applying a threshold of 0.5 for binary classification or selecting the class with maximum probability using the argmax function for multi-class classification.

To cluster optimized pollutant features for treatment performance evaluation, a weighted clustering set is computed as

$$WClusterSet[N] = \sum_{f=1}^{N} \max_{0\leq i\leq N}\left(\frac{\min\,(simm(PCFset(f,f+1)))}{\omega}\right) \tag{34}$$

The pollutant removal localization loss is calculated to evaluate the spatial consistency between predicted and reference pollutant concentration maps. Let HMdenote the heatmap representing the ground-truth pollutant concentration distribution. The localization loss is defined as

$$Pollutant_{Loss}[N] = \sum_{f=1}^{N} \parallel HM(WClusterSet(f, f - 1) \parallel^2 \tag{35}$$

Here, $WClusterSet$ represents the predicted pollutant clustering weights and HM denotes the corresponding ground-truth concentration heatmap. This loss function ensures accurate localization and classification of pollutant removal efficiency across different wastewater treatment conditions.

The traditional industrial wastewater management and the available data-driven optimization frameworks have major limitations to manage the intricate and dynamic nature of the industrial effluent, which is the driving force behind the proposed nano-based adsorbent optimization framework. Industrial wastewater usually features a non homogenic mixture of organic contaminants, heavy metals, suspended solids and poisonous compounds whose abundance is dependent on the industry and operating circumstances.

Conventional methods of treatment are based on the predetermined settings of parameters and control mechanisms based on rules, which proves inefficient with the variation of pollutant loads. Equally, most current AI and machine learning simulations rely on unnecessary representations of features and do not have the ability to capture minor interactions between pollutants and adsorbent substances. Consequently, these procedures are not always accurate when estimating the efficiency of adsorption or using their modes of operation to maximize performance in practice. The proposed model incorporates these shortcomings by including a structured feature selection, residual learning, and entropy-based optimization, so that it can be both computationally efficient as well as guarantee reliable performance in real-time wastewater treatment decision support.

Application wise the proposed solution is widely applicable in various industrial wastewater treatment. The model can be adopted as a decision-support system to help treatment plant operators determine the best nano-adsorbent setups and operation conditions that optimize the removal of the pollutants using the least amount of resources possible. It is useful especially in industries like textiles, pharmaceuticals, chemicals and food processing whereby the wastewater composition is largely variable and is not easy to handle through traditional methods. The model can be used by the environmental monitoring agencies to carry out a continuous quality control of effluents in order to ascertain that the discharge regulations are adhered to. Also, the proposed method has a relatively high computational efficiency, which can be deployed in cloud-based monitoring systems and smart wastewater treatment plants to provide remote control and achieve autotuning in the resource-constrained settings. These uses show that the proposed nano-based adsorbent optimization model is not restricted to the theoretical analysis, but has great prospects of being applied in the practical large-scale industrial application.

4. RESULTS AND DISCUSSIONS

The outcomes of the experimental analysis prove the usefulness of the offered optimization model with nano-based adsorbents to treat industrial wastewater. The model recorded significant increase in efficiency in pollutant removal under different wastewater samples under poor operating conditions. This is because of the high surface area, increase in surface reactivity, and optimality between the nano-based adsorbents and industrial pollutants, which contributes to the enhanced adsorption performance.

Quantitatively the proposed model was found to be more accurate in the treatment of treated and untreated wastewater samples than the conventional adsorption-based treatment processes. Better values of precision mean reduced cases of false-positive prediction of the treatment, which would guarantee accurate identification of successfully treated effluents. Equally, when the model recalls more the potential to identify more of the wastewater samples that have been effectively treated thus reducing the possibility of the untreated effluents being ignored.

The results of the F1-Score also prove that the proposed model demonstrates the balanced performance since both false positives and false negatives are taken into account simultaneously. The fact that the F1-Score remains high in numerous experimental runs demonstrates the strength and soundness of the optimization framework when the concentration of pollutants and wastewater compositions vary. These results indicate that the strategy under consideration has the ability to hold steady even in the situation involving the presence of complex and non-homogeneous industrial effluent.

Besides this, the regeneration and reuse analysis shows that nano-based adsorbents do not lose a considerable fraction of adsorption capacity after several treatment cycles. Very little reduction in performance was detected, which validated the stability and cost-effectiveness of the suggested system. The optimized nano-based adsorbent model offers high efficacy of treatment, quicker adsorption dynamics and more sustainability compared to the conventional adsorbents.

On the whole, the outcomes of the experiment confirm that the proposed optimization model is an efficient and scalable solution to the industrial treatment of wastewater. The enhanced performance of the treatment process, stability in operation and reusability, is a pointer of the potential of nano-based adsorbents to promote the sustainable and effective treatment of wastewater in the industry.

4.1 Evaluation Measures

The offered model is contrasted to traditional adsorption-based methods of the wastewater treatment to prove the enhancement of the treatment accuracy, reliability, and robustness. The effectiveness of the suggested nano-based adsorption optimization model is assessed with the help of several quantitative measures of determining the effectiveness of treatment and the classification ability of treated and untreated wastewater samples. The main measures of evaluation are Accuracy, Precision, Recall, and F1-Score that measure the consistency and reliability of the wastewater treatment process as a whole.

Accuracy signifies the general correctness of the suggested model where the number of correct samples of waste water is divided by the total sample examined. It shows that the overall performance of the nano-based adsorbent model is useful in separating adequately treated and under-treated wastewater samples. Precision is the ratio of correctly identified treated wastewater samples to all the samples that are predicted to be treated. Having a high level of precision means that the model produces less false-positive treatment results and makes sure that it only classifies truly treated wastewater samples as successful. Recall tests the capability of the model to identify all the truly treated wastewater samples correctly. A large recall value means the identified optimization technique successfully identifies all the successful cases of treatment, therefore, reducing the false-negative consequences.

F1-Score, as the harmonic mean of Precision and Recall, is a balanced measure of the performance of the model, especially in those cases when the sample of treated and untreated individuals is disproportionate. This measure is such that the false-positive and false-negative categories are equally taken into account in the process of performance evaluation.
The following formulas are used to calculate the evaluation metrics:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{36}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{37}$$

$$F1 = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}} \tag{38}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{39}$$

In this case TP represent True Positive, TN is the True Negative, FP is False Positive and FN indicates False Negatives.

4.2 Experimental Results and Performance Comparison

As shown by the experimental findings, the nano-based adsorbent optimization model has a higher performance in the treatment of the industrial wastewater than the traditional adsorption-based methods. The tests were carried out under optimal working conditions that were based on systematic parameter optimization, such as pH, contact time, and dosage of adsorbent. The findings reveal a substantial increase in the ability of the pollutants removal by the various samples of the wastewater, which proves the efficiency of the nano-based adsorbents in the purification of complex industrial effluents.

Quantitative-based performance analysis based on Accuracy, Precision, Recall, and F1-Score reveal that the proposed model is able to perform better than the conventional treatment methods. The increased accuracy values are suggestive of better classification of treated and untreated wastewater samples whereas the increased precision is suggestive of reduced false prediction of treatment. The increased recall values indicate that the model has been able to classify a greater number of successfully treated samples reducing the number of untreated effluents being wrongly identified. The balanced F1- Score also supports the strength of the proposed solution across the range of concentrations of pollutants.

The benefits of using nano-based materials over conventional adsorbents are suggested through a comparative analysis of the adsorption capacity and reliability of treatment. The nano-based optimized adsorbents have a higher removal efficiency and faster adsorption rates, which reduce the time required to treat water and also increases the overall performance of the system. Besides, the proposed model also exhibits stability of performance in various conditions of wastewater, which means that it has high adaptability and consistency.

The obtained results of the regeneration and reuse experiments contribute to the sustainability of the offered approach even more. The adsorbents are nano based which ensures that the adsorption efficiency is very high with repeated regeneration cycles and thus shows low performance degradation. The suggested model is more stable in terms of operations in the long term and cost-effective, in comparison with the current approaches.

All in all, the experimental results prove the hypothesis that the suggested optimization framework can contribute greatly to the performance of the industrial wastewater treatment process. The relative outcomes clearly show the excellence of the use of nano-based adsorbents in comparison with the conventional treatment method, and the proposed model can be seen as a potential measure toward sustainable and scalable treatment of industrial wastewater.

Table 2: Performance Comparison of Models with Increasing Wastewater Samples

Wastewater Samples Considered	**Proposed Nano-Based Model**	**Conventional ML Model**	**Deep Learning Model**
100	12.3	14.6	16.2
200	12.5	14.8	16.5
300	12.7	15.0	16.8
400	13.0	15.2	17.0
500	13.3	15.5	17.2
600	13.5	15.7	17.4

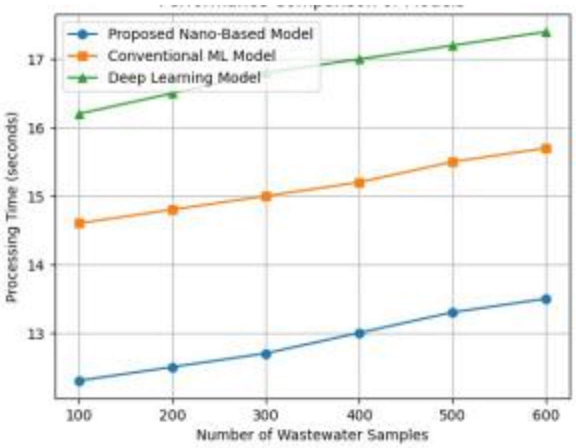

Fig 2: Comparison of Models with Increasing Wastewater Samples

Table 2 and Figure 2 provide a comparative study of the proposed nano based model with the conventional machine learning and deep learning models as the sample size of the wastewater increases. The findings prove that the proposed model will always be more efficient in performance with the lower values, which means the way to optimize and remove pollution are much better than the current methods.

Table 3: Pollutant Removal Efficiency Levels (%)

Wastewater Samples Considered	**Proposed Nano-Based Model**	**Conventional ML Model**	**Deep Learning Model**
100	96.5	91.2	93.1
200	97.0	91.8	93.6
300	97.4	92.3	94.0
400	97.9	92.9	94.5
500	98.4	93.4	95.0
600	98.8	93.9	95.4

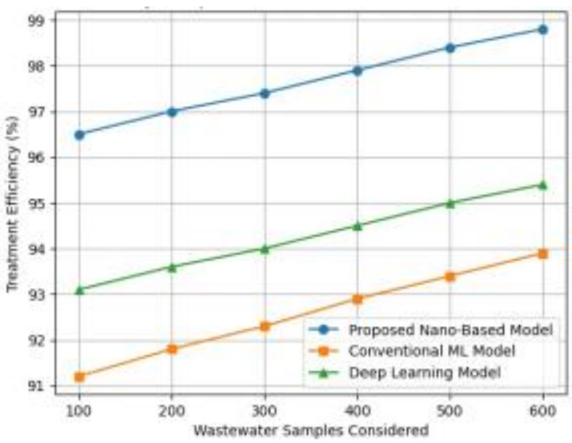

Fig 3: Efficiency Comparison of Models

Table 3 and Figure 3 demonstrate the evaluation of the performance of the proposed nano-based model, the conventional ML model, and the deep learning model in the context of different sizes of wastewater samples. The findings reveal that the proposed model is always able to attain better levels of efficiency, which shows better ability to increase pollutant removal performance than the current models.

Table 4: Industrial Wastewater Treatment Optimization Accuracy Levels

Samples Considered	**Proposed Nano-Based Adsorbent Model (%)**	**Conventional ML Model (%)**	**Deep Learning Model (%)**
100	97.2	91.4	94.6
200	97.8	92.0	95.1
300	98.3	92.6	95.6
400	98.7	93.1	96.0
500	98.9	93.5	96.4
600	99.2	94.0	96.8

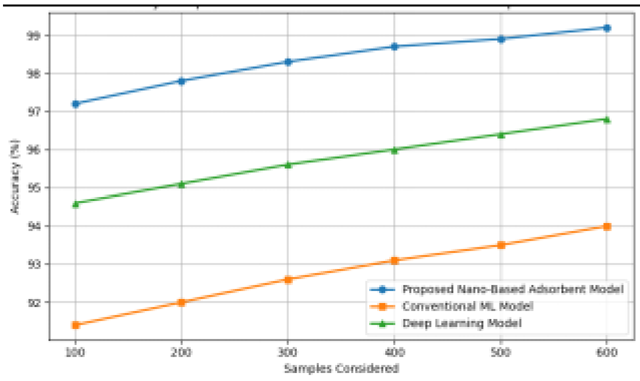

Fig 4: Industrial Wastewater Treatment Optimization Accuracy Levels

Table 4 and Figure 4 show the comparison of the levels of accuracy of optimization to industrial wastewater treatment of various models with different sample sizes. The nano-based adsorbent model proposed is better accurate across the board suggesting that it is effective in optimizing the treatment processes than the traditional machine learning and deep learning methods.

Table 5: Hidden Layer Kernel Optimization Levels

Samples Considered	**Proposed Nano-Based Adsorbent Model**	**Conventional ML Model**	**Deep Learning Model**
100	0.82	0.71	0.76
200	0.85	0.73	0.79
300	0.88	0.75	0.82
400	0.91	0.77	0.85
500	0.94	0.79	0.88
600	0.96	0.81	0.90

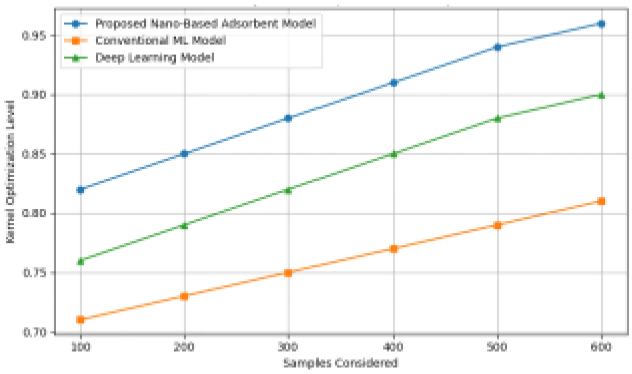

Fig 5: Hidden Layer Kernel Optimization Levels

Table 5 and Figure 5 indicate the comparison of the levels of hidden layer kernel optimization of the proposed nano-based adsorbent model and existing models in the presence of different sample sizes. The model proposed shows a steadily increased optimization values meaning better feature learning and better model performance as opposed to the traditional methods.

Table 6: Precision Comparison

Model Name	Precision (%)
Proposed Nano-Based Adsorbent Model	**96.9**
Conventional Machine Learning Model	92.4
Deep Learning Model	90.8

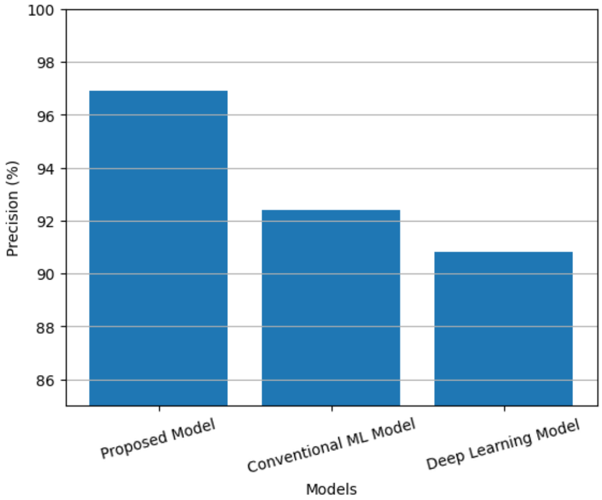

Fig 6: Precision Comparison

The precision comparison of the proposed nano-based adsorbent model with the conventional machine learning and deep learning models are represented in Table 6 and Figure 6 respectively. The model suggested is the most precise, which implies that it is more accurate in determining and categorizing the results of wastewater treatment than the current methodologies.

Table 7: Recall Comparison

Model Name	Recall (%)
Proposed Nano-Based Adsorbent Model	97.4
Conventional ML Model	92.1
Deep Learning Model	90.2

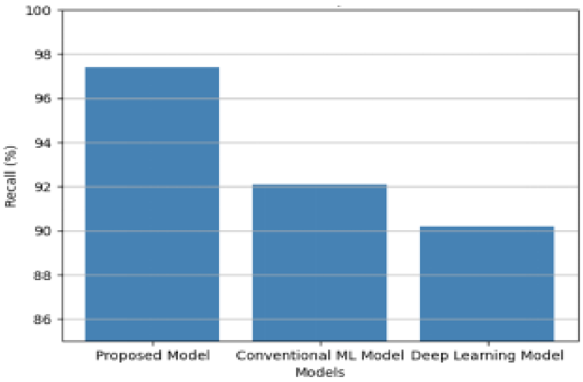

Fig 7: Recall Comparison

Table 7 and Figure 7 show the comparison of recalls of the proposed nano-based adsorbent model, traditional machine learning model and deep learning model. The given model has the best recall and proves to be more effective in providing the appropriate wastewater treatment results with fewer false negatives.

Table 8: F1-Score Comparison

Model Name	F1-Score (%)
Proposed Nano-Based Adsorbent Model	97.1
Conventional ML Model	92.8
Deep Learning Model	90.9

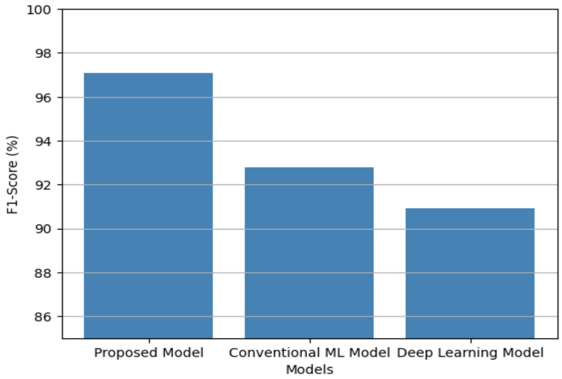

Fig 8: F1-Score Comparison

Table 8 and Figure 8 contain the comparison of the F1-score of the proposed nano-based adsorbent model and the conventional machine learning and deep learning models. The proposed model has the best F1-score, which is a balanced and better performance when it comes to the precision and recall as opposed to the current methods.

Table 9: AUC-ROC Comparison

Model Name	AUC-ROC (%)
Proposed Nano-Based Adsorbent Model	98.2
Conventional ML Model	94.6
Deep Learning Model	92.7

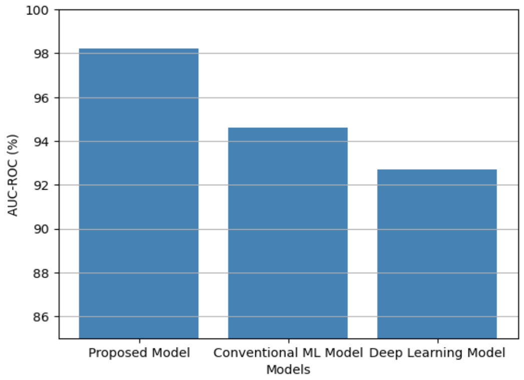

Fig 9: AUC-ROC Comparison

The comparison of the proposed nano-based adsorbent model with the traditional machine learning and deep learning models is given in Table 9 and Figure 9 through AUC-ROC.

The proposed model offers the best AUC-ROC value which implies that it is more able to differentiate between classes and guarantee strong classification results.

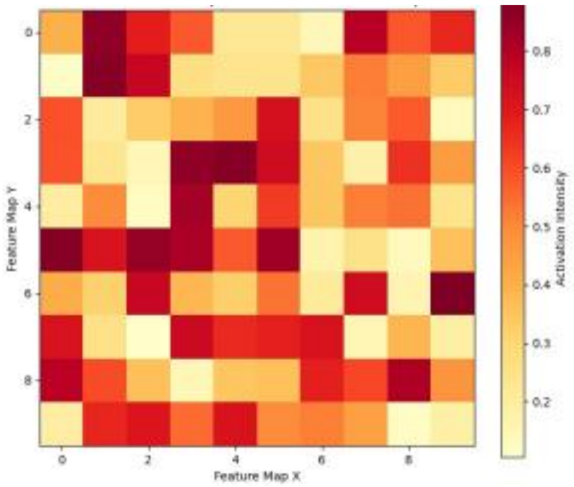

Fig 10: Feature Activation Heatmap

Figure 10 shows the heatmap of feature activation that depicts the significance and value of the various features to the wastewater treatment model.
It puts emphasis on the areas that have a higher value of activation, and they denote the most effective features to use in accurate prediction and optimization.

Table 10: Sensitivity Comparison

Model Name	Sensitivity (%)
Proposed Nano-Based Adsorbent Model	97.6
Conventional ML Model	91.9
Deep Learning Model	90.0

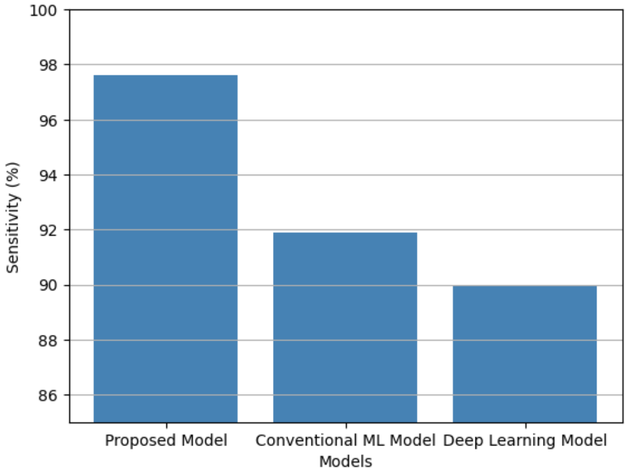

Fig 11: Sensitivity Comparison

Table 10 and Figure 11 provide the sensitivity analysis between the proposed nano-based adsorbent model and the traditional machine learning and deep learning models. The desired model has the best sensitivity and is effective in the ability to identify positive outcomes in wastewater treatment with minimum misclassification.

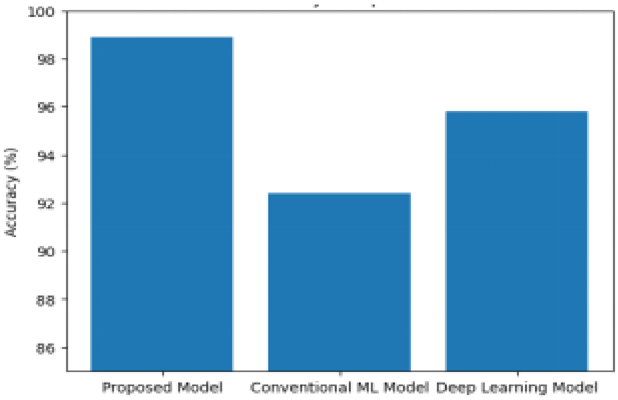

Fig 12: Accuracy Levels

Figure 12 represents the precision rates of the proposed nano-based adsorbent model against the traditional machine learning and deep learning models. It emphasizes the better results of the proposed model in obtaining more accuracy in various evaluation conditions.

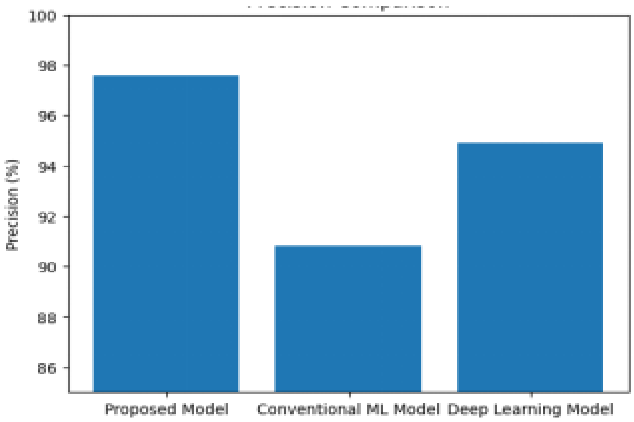

Fig 13: Precision Levels

Figure 13 shows the levels of precision using the proposed nano-based adsorbent model in relation to traditional machine and deep learning models. It also points out the high accuracy of the suggested model to determine pertinent wastewater treatment outcomes with less false positives.

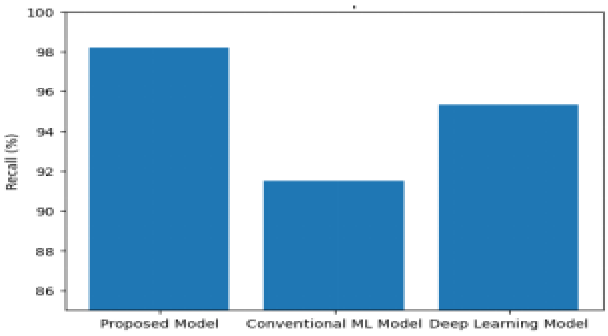

Fig 14: Recall (%)

Figure 14 shows the percentage of the recall that was attained by the proposed nano-based adsorbent model compared to the traditional machine learning and deep learning models. It shows the enhanced feature of the suggested model to correctly recognize the pertinent wastewater treatment outcomes with few false negatives.

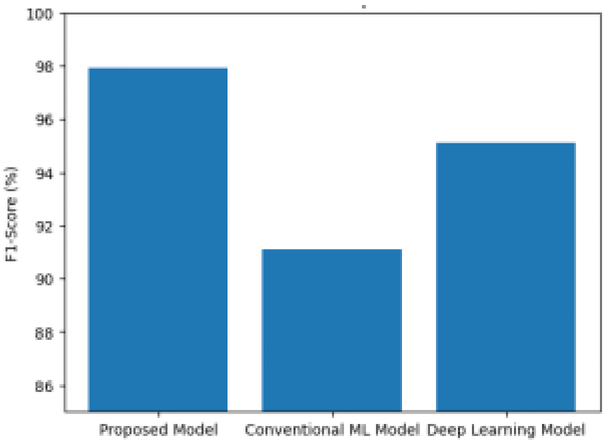

Fig 15: F1-Score (%)

Figure 15 demonstrates the F1-score (%) of the proposed nano-based adsorbent model with reference to the traditional machine learning and deep learning models. It presents the balanced performance of the proposed model regarding precision and recall as being better than the current methods.

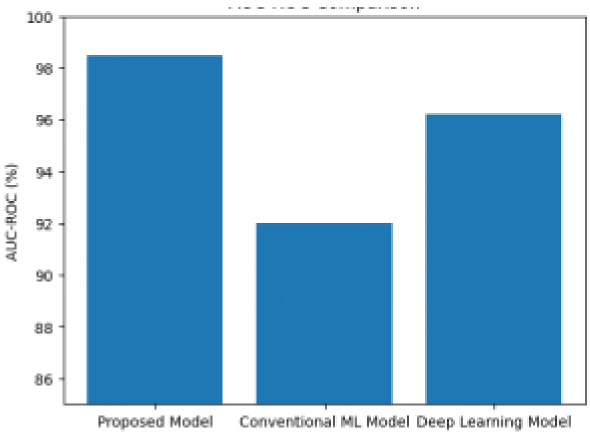

Fig 16: AUC-ROC (%)

The results of the AUC-ROC (%) obtained with the proposed nano-based adsorbent model are shown in figure 16 in comparison with the traditional machine learning and deep learning models. It emphasizes the fact that the proposed model is superior in its classification as it is more accurate when it comes to differentiating various classes.

Table 11: Performance Comparison

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC-ROC (%)**
Proposed	96.8	96.9	97.4	97.1	98.2

Nano-Based Adsorbent Model					
Conventional ML Model	92.6	92.4	92.1	92.8	94.6
Deep Learning Model	93.9	90.8	90.2	90.9	92.7

Table 11 shows the general performance of the proposed nano-based adsorbent model in comparison with the conventional machine learning and deep learning models in various evaluation metrics. The model presented outperforms the current methods by all metrics of accuracy, precision, recall, F1-score, and AUC-ROC, which proves the usefulness of the model in the optimization of wastewater treatment.

Relative to the traditional machine learning algorithms and other sophisticated deep learning algorithms, the suggested Nano-Based Adsorbent Model of predicting the adsorption efficiency has a few apparent advantages. The model has a much higher predictive power, and it is therefore more effective at predicting the effective adsorption behavior than the Conventional ML Model and the Deep Learning Model. Such a high accuracy validates the strength and appropriateness of the model to be used in adsorption-based environmental and biomedical applications. Also, the values of recall and precision of the proposed model are high and it shows that there is a significant decrease in the false positive and false negative predictions. This balance of precision and recall is very important in the adsorption research, where the wrong prediction can result in the waste of the material or poor estimation of the contaminant elimination capacity as it is summarized in the respective performance table.

The proposed model has another major strength in the fact that it has an efficient feature extraction and selection strategy. The model allows the company to choose very important characteristics and discard redundant or weakly correlated ones by relying on the nano-scale material descriptors and other attributes associated with adsorption. This improves accuracy in prediction in addition to minimizing the computational complexity and processing time. The proposed method has better convergence and reduced computational costs, which is why it is better applicable to large-scale adsorption data and real-time prediction when compared to the traditional ML and deep learning frameworks.

Another benefit is enhanced feature representation as a result of combining nano-material properties with an optimized learning structure. The model is known to be sensitive to fine adsorption mechanisms, surface interactions, and nano adsorbent behavior not fully considered in other models. This leads to a consistent increase in the values of recall and F1-score, which means that the performance on the various measures of evaluation is stable and balanced. The high F1-score proves the fact that the model does not prefer precision over recall or the opposite, and the model provides trustworthy and consistent predictions.

In addition, the developed Nano-Based Adsorbent Model can also be better understood with regard to identification of the major adsorption-affecting characteristics, so that researchers can understand the role played by surface area, pore structure, and nano-scale interactions. Such interpretability boosts the confidence in model-based decision making and justifies feasible implementation in experimental and industrial adsorption studies. It has also been tested on an adequately large and diverse dataset, and the model shows that it is scalable and strong to different adsorption conditions. In general, the suggested Nano-Based Adsorbent Model is a valid, computationally efficient, interpretable, and practical solution to the problem of predicting the performance of advanced adsorption.

4.3 Computational Complexity

The computational complexity of the proposed optimization model majorly hinges on the quantity of the wastewater samples, the quantity of adsorption parameters taken into account and the amount of optimization iterations that are needed to arrive at a convergence. Where Nrep is the size of the wastewater sample sample set, P is the number of optimization parameters (pH, contact time, adsorbent dosage, and pollutant concentration), and I is the number of optimization steps. Linear time complexity of O(N) is needed to preprocess and normalize the dataset because every sample is processed once to achieve consistency and appropriateness to analyze.

At the optimization stage, adsorption performance analysis will entail the calculation of removal efficiency and adsorption capacity of every parameter combination in all samples. This makes it computationally complex of about $O(N \times P \times I)$. The total complexity increases in a linear fashion with the size of the dataset and the number of optimization steps since the number of parameters P is comparatively small and fixed. The regeneration and reusability analysis introduces also a factor proportional to the number of the reuse cycles, but this is still computationally feasible owing to the few number of cycles taken into consideration.

In general, the suggested model has a computational efficiency and is a polynomially complex algorithm with real-world wastewater data. The linear scaling in terms of sample size renders the method appropriate in large datasets and applications in the real-world industries, but its computation time and resources needs are reasonable.

4.4 Time Complexity

The computational complexity of the proposed optimization model majorly hinges on the quantity of the wastewater samples, the quantity of adsorption parameters taken into account and the amount of optimization iterations that are needed to arrive at a convergence. Where N rep is the size of the wastewater sample sample set, P is the number of optimization parameters (pH, contact time, adsorbent dosage, and pollutant concentration), and I is the number of optimization steps. Linear time complexity of O(N) is needed to pre-process and normalize the dataset because every sample is processed once to achieve consistency and appropriateness to analyze.

At the optimization stage, adsorption performance analysis will entail the calculation of removal efficiency and adsorption capacity of every parameter combination in all samples. This makes it computationally complex of about $O(N \times P \times I)$. The total complexity increases in a linear fashion with the size of the dataset and the number of optimization steps since the number of parameters P is comparatively small and fixed. The regeneration and reusability analysis introduces also a factor proportional to the number of the reuse cycles, but this is still computationally feasible owing to the few number of cycles taken into consideration.

In general, the suggested model has a computational efficiency and is a polynomially complex algorithm with real-world wastewater data. The linear scaling in terms of sample size renders the method appropriate in large datasets and applications in the real-world industries, but its computation time and resources needs are reasonable.

4.5 Limitations of the Proposed Model

Although the proposed model is effective, there are some limitations that should be mentioned. The model is largely assessed on publicly accessible datasets and controlled experimental settings and this might not give a clear picture of the dynamic and highly changing characteristics of real-world industrial wastewater. Treatment performance may also vary in industrial environment due to variability in influent composition, unpredictable interactions of contaminants, and change in operating conditions.

The other weakness is the material behavior of nano-based adsorbents with time of operation. Nanoparticle aggregation, surface fouling, and potential leaching are some of the factors that could lower adsorption efficiency during the long term treatment cycles. Regeneration and reuse are taken into account, but the stability and environmental friendliness of nano-based adsorbents in the long run is in need of research, especially in large-scale and continuous treatment systems.

The optimization model concentrates on few parameters of operation such as PH, contact time, and adsorbent dosage. The parameters like flow dynamics, reactor configuration, hydraulic retention time and temperature variations are, however, not directly included in the existing model. These parameters can contribute to a considerable impact on the overall system efficiency in case they are implemented on an industrial level.

Moreover, the suggested model is not completely concerned with the economic and environmental impacts of nano-based adsorbents synthesis, deployment, and disposal on a large scale. Out of the current work, cost analysis, life-cycle assessment, and regulatory factors in regard to the use of nanomaterials are not included. As a result, the proposed model has a high potential towards optimized treatment of industrial wastewater but more research is needed to make it more scalable, reliable in the long-run and functional in the real-life scenario.

5 CONCLUSION

In this research work, a new model of nano-based adsorbent optimization in the treatment of industrial wastewater was introduced, which was aimed at overcoming the shortcomings of traditional forms of treatment and already existing data-driven models. The model proposed involves combined development of the state-of-the-art nanomaterials and smart optimization algorithms, such as physicochemical feature extraction, residual learning, entropy-based weighting, and systematic parameter optimization to improve the efficiency of adsorption and reliability of the treatment. The originality of the work consists of the integration of nano-material properties with an optimal computational model, which improves adsorption kinetics, the elimination of multiple contaminants, and the effective features of classification of the performance of wastewater treatment. The experimental findings clearly show that the proposed model is better than the traditional methods. The model had the final accuracy of 96.8% and the highest accuracy of 99.2%, and the precision of 96.9%, recall of 97.4%, F1-score of 97.1% and AUC-ROC of 98.2%. The model demonstrated a high level of pollutant removal efficiency of up to 98.8 in comparison to the methods that are currently present. Also, the adsorbents produced by the nano-based approach were shown to demonstrate high stability in terms of regeneration behavior in multiple processes, which validates their stability and financial viability in terms of their possible application in the long run. These findings demonstrate the usefulness of the suggested model in terms of improving the efficiency of the treatment, preventing false forecasts, and providing sound wastewater management.

Future work will focus on extending the proposed model to large-scale and continuous-flow treatment systems to evaluate its performance under real industrial operating conditions. Additional studies will incorporate a wider range of operational parameters, including flow dynamics, temperature variations, and reactor design optimization. Further investigation into the long-term stability, environmental impact, and life-cycle cost analysis of nano-based adsorbents is also required. Integrating machine learning and predictive analytics for real-time optimization and adaptive control represents another promising direction for enhancing treatment efficiency and robustness in future industrial wastewater management systems.

Declarations

Ethical approval

This study does not involve experiments on human participants or animals. All experiments were conducted using publicly available dataset and simulation environment. Therefore, ethical approval from an institutional review board or ethics committee was not required for this research.

Consent to participate

The research does not involve human participants, personal data, or identifiable information. Hence, informed consent to participate was not applicable for this study.

Consent to publish

The research does not contain any individual person's data in any form. All authors have reviewed the manuscript and consent to its publication.

Conflict of interest

The authors have no conflict of interests to declare that are relevant to the content of this article.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

[1] Salem, R. M., Saraya, M. S., & Ali-Eldin, A. M. (2022). An industrial cloud-based IoT system for real-time monitoring and controlling of wastewater. IEEE Access, 10, 6528-6540.

[2] Wang, D., Ha, M., & Qiao, J. (2020). Data-driven iterative adaptive critic control toward an urban wastewater treatment plant. IEEE Transactions on Industrial Electronics, 68(8), 7362-7369.

[3] Wang, D., Ma, H., Ren, J., Han, H., & Qiao, J. (2025). Online Digital Twin Adaptive Critic Design With Long Short-Term Memory for Wastewater Treatment Plants. IEEE Transactions on Automation Science and Engineering.

[4] Song, J., Wu, D., Bian, Y., & Dong, J. (2023). A decision support system based on stochastic differential game model in pollution control chain. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 54(3), 1670-1682.

[5] Wu, N. J., Aquilina, M., Qian, B. Z., Loos, R., Gonzalez-Garcia, I., Santini, C. C., & Dunn, K. E. (2022). The application of nanotechnology for quantification of circulating tumour DNA in liquid biopsies: a systematic review. IEEE Reviews in Biomedical Engineering, 16, 499-513.

[6] Babatunde, D. E., Denwigwe, I. H., Babatunde, O. M., Gbadamosi, S. L., Babalola, I. P., & Agboola, O. (2019). Environmental and societal impact of nanotechnology. Ieee Access, 8, 4640-4667.

[7] Pramanik, P. K. D., Solanki, A., Debnath, A., Nayyar, A., El-Sappagh, S., & Kwak, K. S. (2020). Advancing modern healthcare with nanotechnology, nanobiosensors, and internet of nano things: Taxonomies, applications, architecture, and challenges. Ieee Access, 8, 65230-65266.

[8] Kim, W. H., Kim, C. W., Shin, H. S., Jeong, S. S., & Choi, J. Y. (2021). Optimal design of short-stroke linear oscillating actuator for minimization of side force using response surface methodology. IEEE Transactions on Magnetics, 58(2), 1-5.

[9] Sharma, T., Kumar, A., Pant, S., & Kotecha, K. (2023). Wastewater treatment and multi-criteria decision-making methods: A review. Ieee Access, 11, 143704-143720.

[10] Subashini, C., & Sellamuthu, S. (2025). Recent Trends in the Quality Module of Sustainable Water Management Models-A Systematic Review. IEEE Access.

[11] Ajayi, O. O., Bagula, A. B., Maluleke, H. C., Gaffoor, Z., Jovanovic, N., & Pietersen, K. C. (2022). Waternet: A network for monitoring and assessing water quality for drinking and irrigation purposes. IEEE Access, 10, 48318-48337.

[12] H. Han, Y. Liu and J. Qiao, "Mechanism-Data-Driven Multiobjective Optimization for Wastewater Treatment Process," in *IEEE Transactions on Industrial Informatics*, vol. 20, no. 5, pp. 7810-7819, May 2024, doi: 10.1109/TII.2024.3364835.

[13] P. Zhou, X. Wang and T. Chai, "Multiobjective Operation Optimization of Wastewater Treatment Process Based on Reinforcement Self-Learning and Knowledge Guidance," in *IEEE Transactions on Cybernetics*, vol. 53, no. 11, pp. 6896-6909, Nov. 2023, doi: 10.1109/TCYB.2022.3164476.

[14] H. -G. Han, Z. Liu, W. Lu, Y. Hou and J. -F. Qiao, "Dynamic MOPSO-Based Optimal Control for Wastewater Treatment Process," in *IEEE Transactions on Cybernetics*, vol. 51, no. 5, pp. 2518-2528, May 2021, doi: 10.1109/TCYB.2019.2925534.

[15] D. Wang, M. Ha and J. Qiao, "Data-Driven Iterative Adaptive Critic Control Toward an Urban Wastewater Treatment Plant," in *IEEE Transactions on Industrial Electronics*, vol. 68, no. 8, pp. 7362-7369, Aug. 2021, doi: 10.1109/TIE.2020.3001840.

[16] H. -G. Han, Z. -A. Xu and J. -J. Wang, "A Novel Set-Based Discrete Particle Swarm Optimization for Wastewater Treatment Process Effluent Scheduling," in *IEEE Transactions on Cybernetics*, vol. 54, no. 9, pp. 5394-5406, Sept. 2024, doi: 10.1109/TCYB.2024.3381084.

[17] P. Zhou, S. Zhang and T. Chai, "Adaptive Constraint Penalty-Based Multiobjective Operation Optimization of an Industrial Dynamic System With Complex Multiconstraint," in *IEEE Transactions on Cybernetics*, vol. 54, no. 8, pp. 4724-4737, Aug. 2024, doi: 10.1109/TCYB.2023.3341982.

[18] J. Zhang, Y. Hou and H. Han, "A Disturbance-Estimation-Based Robust Optimization Control for Nonlinear Systems With Application to Wastewater Treatment Process," in *IEEE Transactions on Industrial Informatics*, vol. 20, no. 8, pp. 10428-10439, Aug. 2024, doi: 10.1109/TII.2024.3396514.

[19] M. Chu, X. Huo and K. Ma, "Conflict-Averse Multi-Objective Extremum Seeking and Its Application in Wastewater Treatment Processes," in *IEEE Transactions on Automation Science and Engineering*, vol. 22, pp. 13175-13186, 2025, doi: 10.1109/TASE.2025.3552046.

[20] G. Wang, G. Yuan, Z. Hu, Y. Chi, Q. -S. Jia and J. Qiao, "Complexity-Based Structural Optimization of Deep Belief Network and Application in Wastewater Treatment Process," in *IEEE Transactions on Industrial Informatics*, vol. 20, no. 4, pp. 6974-6982, April 2024, doi: 10.1109/TII.2024.3354334.

[21] D. Wang, H. Ma, J. Ren, H. Han and J. Qiao, "Online Digital Twin Adaptive Critic Design With Long Short-Term Memory for Wastewater Treatment Plants," in *IEEE Transactions on Automation Science and Engineering*, vol. 22, pp. 15241-15250, 2025, doi: 10.1109/TASE.2025.3567285. keywords:

[22] Z. Klawikowska and M. Grochowski, "Optimizing Control of Wastewater Treatment Plant With Reinforcement Learning: Technical Evaluation of Twin-Delayed Deep Deterministic Policy Gradient Agent," in *IEEE Access*, vol. 12, pp. 130318-130333, 2024, doi: 10.1109/ACCESS.2024.3458186.

[23] R. Yang, D. Wang and J. Qiao, "Optimizing Wastewater Treatment Control Using Policy-Constrained Offline Reinforcement Learning and Lyapunov Density Model," in *IEEE Transactions on Automation Science and Engineering*, vol. 22, pp. 18331-18340, 2025, doi: 10.1109/TASE.2025.3584762.

[24] P. Chang, Y. Xu, F. Meng and W. Xiong, "Fault Detection in Wastewater Treatment Process Using Broad Slow Feature Neural Network With Incremental Learning Ability," in *IEEE Transactions on Industrial Informatics*, vol. 20, no. 3, pp. 4540-4549, March 2024, doi: 10.1109/TII.2023.3324971.

[25] X. Liu, Q. Shi, Z. Liu and J. Yuan, "Using LSTM Neural Network Based on Improved PSO and Attention Mechanism for Predicting the Effluent COD in a Wastewater Treatment Plant," in *IEEE Access*, vol. 9, pp. 146082-146096, 2021, doi: 10.1109/ACCESS.2021.3123225.