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Quality Prediction of Treated Water in Sewage Treatment Plant Using Machine Learning

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Abstract
The purpose of the proposed study is to examine the viability of employing treated sewage water in a variety of domestic companies' industrial applications. The Support Vector Machine (SVM), Artificial Neural Network (ANN), and K-Nearest Neighbor machine learning models were used in this study to classify the water quality after sewage treatment in sewage treatment plants (K-NN). First off, several stages of the sewage treatment facilities' data base have been gathered. Second, a feature extractor and selection procedure employing Principal Component Analysis has been implemented for the subsequent procedure (PCA). As a final step, various machine learning models are trained to classify the treated water. The suggested methodology is the ideal way to automatically classify treated water so that it can be used for various industrial purposes in the future.

Keywords: *Machine Learning, Sewage Treatment Plant, Quality Prediction, SVM, ANN, K-NN*

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I. INTRODUCTION

The main goals of wastewater management and treatment are to protect the environment, manage it in a way that makes it sustainable and fit for habitation, as well as to make sure that the threat posed by wastewater does not jeopardise public health. Treatment ensures that the treated wastewater cannot pollute the environment, harm aquatic life, or harm the general environment when it is released into water bodies. The goal of the treatment facility is to hasten the natural water purification process. filtration. The most common techniques for reducing water pollution are the use of sewage systems and water treatment facilities. Municipal wastewater is collected by sewers from residences, workplaces, and industries and transported to a treatment facility where advanced equipment treats the wastewater in stages according to its composition.

Depending on the circumstance, wastewater may be defined as potable water that has been contaminated by microbial chemicals produced or naturally present as a result of human, commercial, or industrial activity. Depending on the municipality's population, the number of industries present, the degree of separation between rainwater and hygienic fluids, and the depth of groundwater sources, the characteristics of wastewater discharges would vary greatly [1]. Domestic wastewater is any wastewater that people unintentionally or intentionally pour down the drain, including wastewater from the kitchen, bathroom, and laundry. Sanitary fluids or water includes domestic wastewater as well as wastewater discharged from commercial facilities and other sources. The diagram below shows how the sewage treatment plant is conceptualized.Groundwater, surface water, storm water, and industrial, commercial, and domestic water use are the main sources of wastewater. The two main types of wastewater sources are residential streams and non-residential or commercial sources. The mass of it originates from domestic activities like washing clothes, using the toilet, cleaning the dishes, watering our lawn, and even taking showers [2]. According to industry sources, we provide a range of extra liquid waste services, as well as industrial, commercial, and institutional clients. A unique demand for treatment results from the wastewater produced by corporations, industries, and institutions. Since it contains more complicated pollutants than residential wastewater, industrial, commercial, and institutional wastewater has a very distinct demand for treatment facilities. As a result, treatment expenses are frequently higher. Most modern sewage systems are autonomous in nature, as opposed to historical sewage systems, which combined storm and sanitary water in a single system.The most common methods for reusing water Irrigation, industrial usage, surface water replenishment, and ground water recharge are all factors to consider [3-4]. Watershed features, climatic and geohydrology parameters, the degree of water use for various purposes, and the degree of direct and indirect water reuse all influence the amount of water moved through each channel. Patient safety, construction, economy, aesthetic and most significantly, public acceptance should all be considered while designing a water reuse loop. Given the complexities of sewage reuse projects, the essential considerations must be made for a successful execution of a sewage treatment plant.

Water is an extremely valuable resource and a necessary essential for human life. As a result, it is vital to fulfill the need for water availability as the population grows. 'RECYCLE and REUSE' of wastewater would be a suitable 'BALANCING ACT.' This will allow water to be reused rather than being discarded as "waste."
The trying to follow are some of the explanations why sewage reuse is a feasible alternative:

1. Sewage is a widely obtainable resource.
2. Water is a problem — accessibility is a problem, and there is a lot of competition from all sectors — the only accessible supply is sewage.
3. Due to rapid urbanization and rising water consumption, cities are having difficulty obtaining the needed amount of water.
4. A shortage of natural water bodies inside the city

Given these facts, water recycling and reuse should be made mandatory, and the necessary efforts should be emphasized. Before establishing a wastewater treatment plant, examine factors such as the availability of essential technology and its price, environmentally friendly technology, funding patterns, compliance with guidelines and legislation, and so on.

This paper proposed a study to examine the viability of employing treated sewage water in a variety of domestic companies' industrial applications. The Support Vector Machine (SVM), Artificial Neural Network (ANN), and K-Nearest Neighbor machine learning models were used in this study to classify the water quality after sewage treatment in sewage treatment plants (K-NN).

The remaining paper is as follow, Section II discussed the literature review of the proposed manuscript, Section III, discussed the proposed methodology and Section IV is discussed the result and discussion. Finally, the paper is concluded in the section V.

II. LITERATURE REVIEW

Water covers two-thirds of the earth's surface and makes up 75 percent of the human body, so it's apparent that it's one of the most important components for life on the planet. Water flows through the soil in the same manner that it does in the human body, delivering, dissolving, and renewing nutrients and organic materials while also conveying waste. The loss in marine and riparian life populations, the growth of green algae in rivers, and the stink and slime that results from putrefaction in the water are all apparent indicators of the depth and breadth of the ecosystem's disturbance. By filtering wastewater effluent, sewage treatment plants can assist to prevent pollution from entering waterways. By filtering wastewater effluent before it enters a water body, sewage treatment facilities can assist to prevent pollution from entering rivers. As a result, research into sewage treatment plants is a vital first step in identifying solutions for decreasing river pollution and, as a result, environmental contamination. The chapter will examine and expose crucial in information about sewage treatment plant assessment, water contamination concerns, system importance, and other topics.

Water pollution is the direct or indirect introduction of harmful substances into surface or ground water. Hydrologic effects are alterations in groundwater and surface water flows (streams and rivers). The sight and smell of seriously polluted waterways served as some of the early inspiration for the environmental movement in the 1970s. About a century prior to that, the dangers of dirty water to human health sparked what became known as the "sanitary revolution" in Europe and the United States, giving clean water supplies and sewage systems in cities priority. Despite great advancements in river sanitization, water pollution remains a serious global issue today. It affects the condition of freshwater ecosystems and the societies that depend on them.

Carball et al., 2004 [1] A group of 13 PPCPs connected to diverse chemicals (musks, drugs, and hormones) were used as a sign of the existence of this contaminant in the municipal municipal wastewater produced by a Galician city of around 100,000 people (Northwest Spain). This study's primary objective is to evaluate their fate along the different units in order to evaluate possible improvements for increasing extraction efficiency. The majority of the few appears to work on this topic discovered in the literary works concentrate on the overarching removal of PPCPs along STPs (distinction between effluent and influent loads). The eight components that were discovered in raw wastewaters exhibited various behaviours as they moved through STP units:Vieno et al., 2005 [2] When the river was coated in ice and snow, pharmaceuticals were transported further downstream from the STP. A rapid transit of medications was found with a significant rise in water flow rate (i.e., during snow melting). In the winter sample, the DWTP downstream from the STP generated water with roughly 8 ng L-1 of ibuprofen and ketoprofen, however in the spring and summer samples, the researched pharmaceuticals were not discovered in the drinking water. The findings reveal that cold seasons in boreal locations can significantly raise the danger of pharmaceutical contamination in the environment as well as the risk of drinking water contamination.Go´mez et al., 2007 [3] The proposed analytical approach, which used SPE followed by GC–SIM–MS, provided for a simple, quick, and reliable assessment of the reported chemicals at the concentration levels found in the samples. The results of a one-year monitoring research detailed in this paper show that a set of 14 chemicals are resistant to the traditional water treatment techniques used in sewage treatment plants. The substances investigated, mostly pharmaceutically active compounds, were found in treated waters, indicating that they constituted a continual input to coastal areas receiving STP discharges.

Rajbanshi et al., 2008 [4] Heavy metal removal from wastewater necessitates advanced chemical technologies and is therefore more costly. Bioremediation with heavy metals resistant microorganisms is a less expensive approach. Heavy metals are present in high concentrations in raw wastewater, which are not destroyed by the traditional wastewater treatment procedure. Metal processing, mining, and electroplating, as well as tanning, carpet washing, and dyeing, are the primary sources of heavy metals. The presence of excessive levels of harmful heavy metals in wastewater causes pollution of receiving water bodies as well as negative effects on aquatic life.Stamatis et al., 2010 [5] This study investigates the existence and removal of widely used fungicides in primary (mechanics), secondary (sludge), and intermediate (sand filter and chlorination) municipal sewage treatment facilities that accept mixed sewage discharges. Compounds from the triazole and anilino-pyrimidine families were among the analytes studied. Solid-phase extraction was used to determine the composition of wastewaters and river water samples, followed by gas chromatography with flame thermionic and mass spectrometric detection. All azole fungicides including pyrimethanil had relatively poor removal efficiency following secondary and tertiary applications, with the exception of triadimefon. The fungicides were removed at a rate of 31 percent for pyrimethanil and 65 percent for triadimefon following additional treatment. The average total elimination efficiencies following tertiary treatment for pyrimethanil and triadimefon were 46 percent and 93 percent, respectively. The data show that large amounts of fungicides infiltrate river waters, and that municipal wastewater treatment methods only decrease some of these chemicals to low levels.Xu et al., 2015 [6] Antibiotics and antibiotic resistance genes were found in a sewage treatment facility and its effluent receiving river water in Beijing, China, in this investigation. During the STP operations, the three classes of antibiotics were largely removed, and the concentrations of the chosen ARGs were kept reasonably consistent throughout the treatment procedures. Only sections of ARGs were associated with the amounts of particular antibiotics, according to correlation analysis. The quantities of antibiotics and ARGs in the receiving river were lower than in the effluents, but the majority of antibiotics and ARGs came from the STP, suggesting that the STP was a significant repository of both antibiotics and resistance genes.Stamatis et al., 2017 [7] Wastewater treatment at waste disposal facilities results in the production of sewage sludge. The two basic types of sludge are primary sewage and treating waste, also referred to as sludge in the context of the activated sludge. Sewage, also referred to as municipal sewage sludge (MSS), is a muddy waste that can be solid, nearly fully, or liquid. The majority of it is composed of proteins, polysaccharides, detergents, phenols, and lipids, but it also includes harmful and deadly chemical and inorganic pollutants. Wastes from homes and businesses combined with more than 99 percent water constitute sewage. It is produced by residential, institutional, industrial, and industrial operations. Sewage treatment is the process of removing pollutants from wastewater, particularly residential sewage. It employs physical, chemical, and biological processes to get rid of these pollutants and produce treated wastewater that is acceptable to the environment. The three phases of therapy are pretreatment, treatment, and tertiary treatment. During pretreatment, large solids and grit are filtered away. In basic treatment, the water is allowed to stand so that sediments can sink to the bottom and oils and fats can rise to the top. In secondary treatment, sludge digesters are utilised to further treat the waste. Cao et al., 2020 [8] Wastewater treatment along the coast are a major source of microplastics entering the marine environment. The intra-day variation in microplastic richness in the prominent should be significant and may have a significant impact on their estimation of the daily mass load because sewage is so closely related to human activities. At a second WWTP in Hong Kong, an experiment with 2-hour interval sampling was run to examine intra-day variations and daily loads of nanoplastics in influent. The average amount of microplastics per litre increased from 7.1 6.0 to 12.8 5.8 particles/L over time, with the most prevalent particle sizes falling between 1 and 5 mm. Polyethylene and polyester made up around 80% of the microplastics in samples taken between 9:30 and 15:00, whereas polypropylene and polyurethane made up the majority of samples collected after 17:00. Microplastic loads varied significantly from day to day, ranging from 6.60 108 to 1.16 109 particles/ day, implying that computed daily microplastic loads based on a given sample interval may underestimate the real daily load.Brunschet al., 2018 [9] Soil retention filters that have been used in the past. Organic micropollutants can be removed using traditional retention soil filters. The organic matter removal was better in the upper retention soil filter layer, which contained the greatest organic matter. This suggests that the presence of organic materials aids in the elimination of organic micropollutants. This implies that compared to technical treatment systems like activated carbon filtration or ozonation, this traditional retention soil filter, the natural system, has a longer start-up period. - Organic micropollutant removal is influenced by contact time, with prolonged impounding in the winter resulting in greater removal. Retention soil filters would be used to their full potential if operational circumstances were tailored to removal kinetics. - In contrast to technical post-treatment measures, the typical retention soil filter's cleaning ability for organic micropollutants increases rather than decreases with time. This demonstrates the natural system's sturdiness. In organic enriched layers in the retention soil filter, sorption and biodegradation may be improved. There was a trend toward better removal over the summer, indicating that biodegradation had a role in the removal.Wanget al., 2022 [10] The adsorption process for treating wastewater is a complicated process that is easily influenced by influent quality, aeration time, and other variables, resulting in unstable effluent. In China, where sewage discharge rules are becoming increasingly strict, it is vital to develop a prediction model for early warning of effluent quality. Nine machine learning techniques were used to build models for the prediction of effluent Chemical Oxygen Demand in this study (COD). Model optimization was carried out by trying to introduce the hysteresis situation, information processing method (K-FOLD), and process parameters [dissolved oxygen (DO), sludge return ratio (SRR), and mixed liquid suspended solids (MLSS)] in attempt to optimize the forecasting model accuracy. All these Gradient Boosting Decision Tree (GBDT) and K-Nearest Neighbour (KNN) had good prediction effects, with the best MAPE, RMSE, and R2 scores of 7.34 percent/1.29/0.92 respectively (COD, KNN). The improved models were then used to forecast total phosphorus (TP), total nitrogen (TN), and pH in effluent. MAPE/RMSE/R2 values were 7.43 percent /0.92/0.93 (TN, GBDT), 17.81 percent / 0.19/0.99 (TP, KNN), and 0.53 percent /0.16/0.99 (pH, KNN), suggesting great prediction accuracy. Changes in modelling circumstances, as well as comparisons across them, provide wastewater prediction models a new perspective. Furthermore, this research is relevant to the real-world operation and administration of WWTPs, laying the groundwork for the re-regulation of sewage treatment plant energy savings and consumption reduction (WWTPs).Ostmanet al., 2019 [11] In typical sewage treatment facilities, some micropollutants have low removal efficiency and thereby penetrate the aquatic environment. A variety of additional treatment procedures are now being explored to minimize the quantities of pollutants in the environment in indicating the level, and hence the impacts on biota. Ozone treatment and absorption onto activated charcoal are two such processes. The effectiveness of Sweden's first comprehensive ozonation treatment facility in eliminating antibiotics, designed to compensate, and biocides was evaluated in this study. On a pilot scale, the effects of introducing granular activated carbon (GAC) and pilot-scale ozonation were also assessed. With exception of benzotriazoles and candidiasis, the standard treatment (13,000 PE) with full-scale color removal (0.55 g O3/g Total organic material (TOC)) was able to remove the majority of the chemicals examined (N90%) (b50 percent). On a pilot scale, adsorption on GAC exhibited a better removal effectiveness than ozonation (N80 percent for all studied compounds). Three distinct forms of GAC were tested, and various removal rates were discovered. The GAC with the lowest particle sizes, in particular, had the best removal efficiency. The findings show that choosing the right type of carbon is critical for achieving highly specific component removal goals.Yanget al., 2021 [12] Water treatment facilities are a major source of micro - plastics (MPs) in the environment, although their distribution and properties in WWTPs remain unknown. To supplement research on the destiny of MPs in interior China, the study looked at the transport, properties, and fate of MPs in both wastewater and waste from WWTPs in Xi'an, a western province of China. As a result, the metallurgy microscope and Spectroscopy spectrometer were used to examine and evaluate the quantity, size, shape, colour, and type of MPs in sewage and sludge from various treatment techniques. The concentration of MPs with distinct properties changes continually during the primary treatment, resulting in variances in MP dispersal in sludge and sewage. Domestic sewage is still the largest source of micro - plastics in Beishiqiao water treatment facility, according to MP characteristics. In the building of MPs pollution, limiting the use of plastic items in daily life or developing alternatives is critical.Cooperet al., 2022 [13] The discharge of refers to the water from sewerage systems is a major form of nitrogen (N) and phosphoric (P) enrichment, however tertiary treatment procedures such as P-stripping have been demonstrated to reduce the risk of eutrophication. The goal of this study was to assess the effects of sewage effluent released from sewerage systems Ps with varying tertiary treatment classes on nutrient oscillations to across River Wensum catchment in the United Kingdom. Between January 2009 and October 2013, river water samples were collected at monthly intervals from 20 sites around the watershed, totaling 677 samples that were analyzed for a variety of hadrochemical characteristics. These results were attributable to P-stripping facilities servicing bigger populations, which released a higher effluent P load, suggesting that tertiary P-stripping alone is unable to offset population pressure and ensure rivers reach satisfactory hadrochemical state.

III. DATA COLLECTION AND PROPOSED METHODOLOGY

Research project completion is aided by systematic information gathering. The information is kept on file to help with identifying the traits of the plant. The 3BRD Sewage Treatment Plant (STP), which spans 50 MLD in Sector 47 as shown in Fig.3.1, is chosen from among all of the residential effluent plants that are now accessible in Chandigarh based on the availability of data from the last three years. The technique offered by M/s. Ramky Infrastructure Ltd. is based on the STP's Cyclic Activated Sludge Technology component from SFC Environmental Technology Pvt. Ltd., a leading provider of wastewater treatment technology worldwide. Table1 provides a detailed description of the sewage treatment facility.Industrial wastewaters can differ greatly in both internal and external properties. Industrial discharges' effects are influenced by specific pollutants in the atmosphere as well as their general features, such as dissolved oxygen and particle concentration. There are three options for handling industrial drainage. Control can take place at the facility's site of origin; wastewater can be treated within the plant and then recovered or dumped directly into wastewater effluents if it was previously intended for disposal to public treatment sources. The raw sewage and treated sewage water utilized data spans more than three years from Chandigarh's sewage treatment plants, or from 1 October 2016 to 31 December 2019. To extract the pertinent data from the untreated sewage and processed sewage water from sewage treatment plants, five crucial parameters are acquired in this study. The implementation uses the obtained raw data sets of the three situations (S1-raw sewage water, S2-primary treated water, and S3-outlet treated water).

Table 1 Detailed description of Chandigarh's sewage treatment facilities

Full Capacity	50 MLD
Spread Area	48 acres
Peak factor	2.25
Flow rate	43000 cum/day

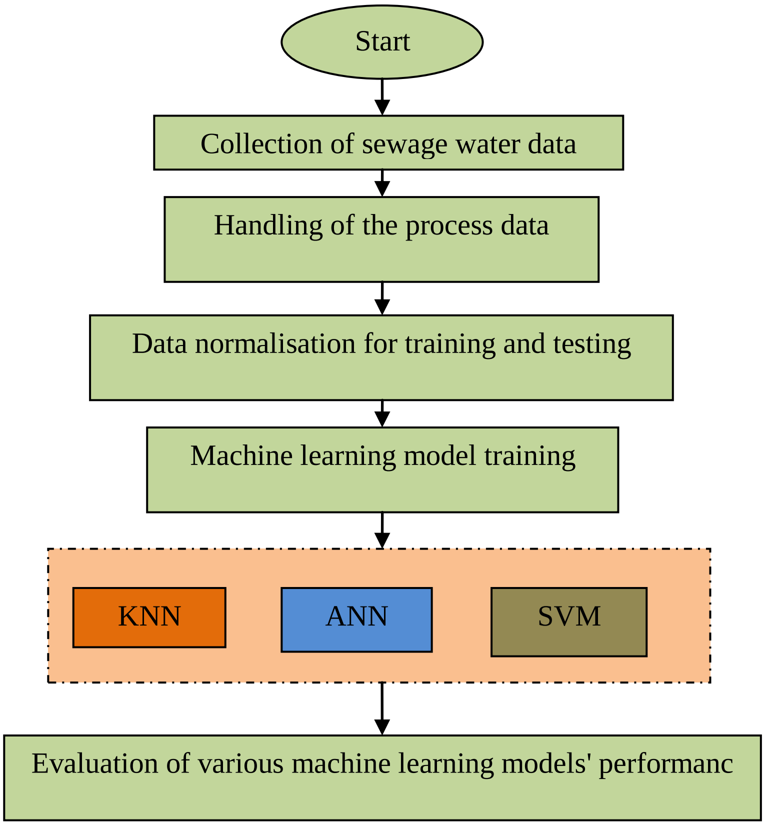


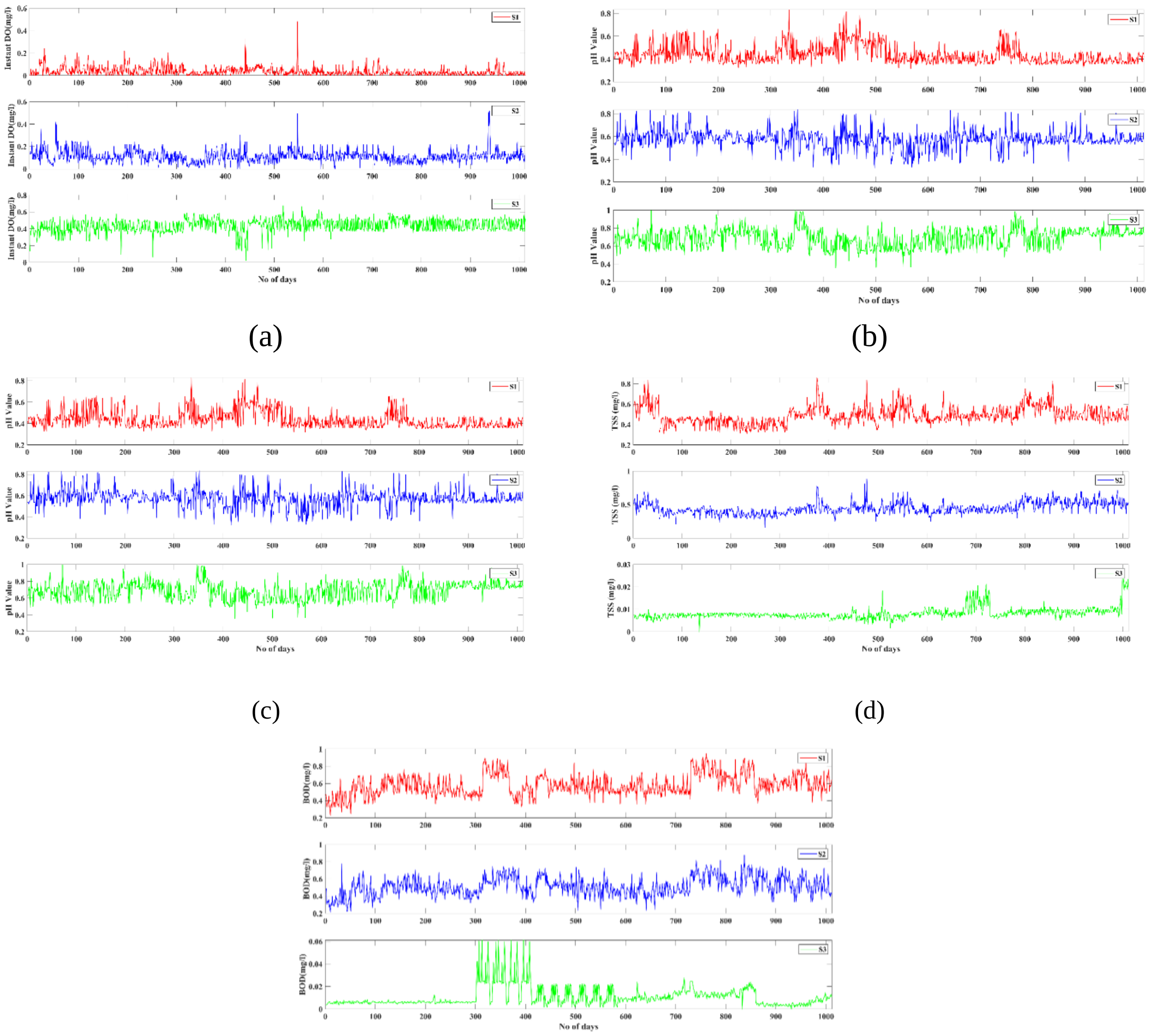
Fig.1 Flowchart of the Suggested Methodology

Despite the fact that it only gets about 48 MLD of sewage, the Sewage Treatment Plant now has a 50 MLD capacity. Three processes are used to handle the water that is delivered to the STP: primary, secondary, and tertiary. The Sewage Treatment Plant receives 48 mgd of water; 35 mgd of it is treated to the secondary level, while the final 10 mgd is treated to the tertiary level. The city receives the sewage that has undergone tertiary treatment and uses it to water gardens and green spaces. Population growth and rising water use have led to an increase in waste flow. This necessitated expanding the water treatment system. To treat wastewater and discharge treated sewage into the free choe, construction of a 5 mgd water treatment plant has started at Raipur Kalan. As they are in surface water treatment for a source of potable water, water purification, subsidence, filtration, and disinfection are standard management methods and operations for reuse in these situations. The preservation of the treated wastewater is ensured by the high level of microbial clearance attained by a well-managed treatment facility.

This section explains the proposed work's methodology in preparation for the portion that will follow (i) Data gathering, data handling, and training of machine learning models are all included. Fig.1 depicts the proposed methodology's flowchart.

IV. RESULT AND DISCUSSION

This section illustrates the validation of the work that was put into place for the classification of the treated water quality in sewage treatment plants. Chandigarh, India's sewage treatment plants provided the results of the analysis, which were used to segment the treated water data into three distinct conditions. As a quality indicator for both treated and untreated sewage water, a few common features or parameters have been utilized, including immediate do, pH value, TSS, COD, and BOD. Finally, this enormous amount of data is utilized to train machine learning models like SVM [14-16], ANN [17-19], and K-NN [20-22] for more accurate categorization of treated and untreated sewage water in wastewater treatment plants. Three classifiers—ANN, SVM, and K-NN—have been compared in this research effort, and it has been found that KNN has the highest accuracy.



(a) (b) (c) (d) (e)

Fig.2 The number of days affects different parameters (a)instant do values. (b) pH (c) TSS (d) COD (e) BOD

The sewage treatment plant's physical inspection revealed that the industry uses roughly 600 cu m of water each day. 90% of the accessible raw water use is provided by storage tanks from outside town bore wells. Each tanker of water, which has a volume of 10 cum, costs Rs. 150. As a result, the corporation shells out a lot of cash to purchase raw water from bore wells located outside of the town. The potential use of treated sewage water from a nearby municipal facility was looked into as a different source of water demand. We looked for a technically workable and financially viable solution for the benefit of the company and the conservation of water, a precious natural resource. The untreated sewage and processed sewage water utilized data spans more than three years from Chandigarh's sewage treatment plants, or from 1 October 2016 to 31 December 2019. In this study, the essential data are gathered from the raw sewage and processed sewage water from wastewater treatment plants using five main features. Before being used in implementation, the acquired raw data sets for all three circumstances (S1-raw sewage water, S2-primary treated water, and S3-outlet treated water) are properly normalized.Fig.2show the normalized values of the immediate pH and do values, TSS, COD, and BOD, respectively. Every feature's value is plotted in relation to the number of days that raw sewage and treated sewage water from wastewater treatment plants were collected.

Table 2 Confusion matrix for three different treated water quality conditions using SVM

True Class	S1	S2	S3	TPR	FNR
S1	88.9%	11.1%	0%	88.9%	11.1%
S2	10.4%	89.6%	0%	89.6%	10.4%
S3	0%	0%	100%	100%	0%

Predicted Class

Table 3 Confusion matrix for three different treated water quality conditions using SVM

True Class	S1	S2	S3	TPR	FNR
S1	88.9%	11.1%	0%	88.9%	11.1%
S2	10.4%	89.6%	0%	89.6%	10.4%
S3	0%	0%	100%	100%	0%

Predicted Class

Table 4 Confusion matrix for three different treated water quality conditions using SVM

True Class	S1	S2	S3	TPR	FNR
S1	90.8%	9.2%	0%	90.8%	9.2%
S2	9.2%	90.8%	0%	90.8%	9.2%
S3	0%	0%	100%	100%	0%

Predicted Class

Several applications for machine learning techniques are found in sewage treatment plants. The sewage treatment process consists of a number of processes, each of which has a separate stage. These stages can fail for a variety of reasons, including pipeline leaks, flow rate fluctuations, unexpected changes in organic loading, etc. The classification of treated and untreated sewage water in sewage treatment plants is the main emphasis of this thesis study. First, a few common characteristics or metrics, such as the pH value, TSS, COD, and BOD, have been used to gauge the quality of both treated and untreated sewage water. Finally, this enormous amount of data is utilized to train machine learning models like SVM, ANN, and K-NN for more accurate categorization of treated and untreated sewage water in sewage treatment plants. Cross fold validation and holdout validation are two separate validation techniques used to evaluate the effectiveness of the machine learning model. The suggested machine learning method effectively categorizes treated water in intricate environmental systems.

A supervised classification method called SVM use categorization to resolve issues involving two or more categories. A large, labelled training dataset is necessary to train the SVM in order to maximize the adaptive generating capability of the learning machine. Minor errors on constrained training datasets preserve the same minor errors on independent test datasets. Five standard characteristics, such as pH value, TSS, COD, and BOD, have been employed as quality indicators of both treated and untreated sewage water through full adoption. Finally, this huge data is used to train the SVM model for father classification of the treated and raw sewage water in sewage treatment plants with higher classification accuracy. The results of classification accuracy in the term of confusion matrix of the SVM classifier of is shown in Table 2. also, the true positive rate (TPR) and false negative rate (FNR) are discussed in term of accuracy. It can be seen that9the developed method9is able9to9classify9into three mention conditions of treated water accurately. As shown in Table 4.1, the classification of the S3 (outlet treated water) is classify 100% but model has a little bit confused between S2 (raw sewage water) and S2 (primary treated sewage water), which 88.9 % and 89.6 % respectively. Therefore, it can be stated that the proposed intelligent system based on SVM model for treated water quality inspection has able to classify with good classification accuracy on the collected dataset.

An ANN is constructed from hundreds or even thousands of processing units, which are artificial neurons connected by nodes. These processing units are made up of input and output units. The neural network attempts to learn about the data provided in order to produce one output. The input units receive various forms and structures of data based on an internal weighing mechanism. Five standard characteristics, such as pH value, TSS, COD, and BOD, have been employed as quality indicators of both treated and untreated sewage water through full adoption. Finally, using this enormous amount of data, an ANN model is trained to more accurately classify treated and untreated sewer water in treatment facilities. Table 3 displays the classification accuracy findings for the ANN classifier in the condition of confusion matrix. Additionally, the accuracy of the true positive rate (TPR) and false negative rate (FNR) is reviewed. It is clear that the devised approach can accurately classify treated water into the three mentioned states. As can be seen in Table 4.2, S3 (outlet treated water) is classified at 100%, but S2 (untreated wastewater) and S2 (primary treated sewage water), which are classified at 91.4% and 90.1% respectively, are a little bit more confusing in the model. As a result, it can be said that the suggested intelligent system that relies on ANN model for processed water quality assessment was able to identify with respect to the gathered dataset with a high degree of classification accuracy.

Table 5 SVM ANN and K-NN algorithms at various fold cross validation

Fold Cross Validation (%)	**SVM (%)**	**ANN (%)**	**K-NN (%)**
2	92.4	91.7	92.7
4	92.9	92.4	93.0
6	92.4	92.3	93.3
8	91.9	92.6	93.1
10	92.3	92.6	93.3

Table 6 SVM ANN and K-NN algorithms at various holdout validation

Holdout Validation (%)	**SVM (%)**	**ANN (%)**	**K-NN (%)**
15	90.5	93.8	93.8
20	92.8	91.6	92.8
25	92.6	92.2	92.5
30	91.6	92.4	91.9
35	92.4	92.0	92.3

The non-parametric classification method KNN is used for data categorization and regression. In both cases, the input comes from the data set's k closest training examples. Whether k-NN is used for classification or regression will affect the outcome. Through widespread adoption, five common traits—pH value, TSS, COD, and BOD—have been used as quality markers for both treated and untreated sewage water. In order to classify treated and untreated sewage water in sewage treatment facilities more accurately, this large amount of data is used to train the KNN model. The classification accuracy results for the KNN classifier are shown in Table 4.2 along with explanations of the true positive rate (TPR) and false negative rate (FNR) for classification accuracy. It is obvious that the developed method can accurately categories treated water into the three states mentioned. As can be seen in Table 4 S3 (outlet treated water) is classified with 100% accuracy, whereas S2 (raw sewage water) and S2 (primary treated wastewater) are classified with 90.8% accuracy in both scenarios. As a result, it can be said that the suggested intelligent system, which is based on a KNN model, outperforms SVM and ANN in regard to overall classification results for treated wastewater quality inspection and is able to classify with a high degree of accuracy using the dataset that was gathered.

SVM, ANN, and KNN classifiers were compared based on how well they classified treated and untreated sewage water in sewage treatment plants. In both cases, the KNN's results at cross fold validation data outperform SVM and ANN, as explained in Table 5. As shown in Table 6. the results of the KNN and ANN are superior to SVM in terms of classification accuracy, but overall, the KNN outperforms ANN and SVM in terms of cross-fold and holdout validation. By utilizing these powerful machine learning models for sewage treatment, plant managers will be able to maximize the performance of their systems by fostering knowledge creation and sharing decision-making experiences.

V. CONCLUSION

This study created a practical machine learning model for categorizing the treated water quality from sewage treatment plants. The suggested method is based on a machine learning model and enables sharing an automated decision-making system that will improve the efficiency of sewage treatment plants as a whole. The three conditions of treated water quality from the sewage treatment plants (S1-raw sewage water, S2-primary treated water, and S3-outlet treated water) were examined by the authors. Furthermore, the three different classifiers ANN, SVM, and K-NN are given access to all six features. For classifying treated water quality, it was found that the KNN performed better than the SVM and ANN in regard to classification accuracy. Each classifier is put through a variety of cross fold and holdout validation tests. It has been found that, in both scenarios of fold validation set and holdout validation, the KNN has the highest classification accuracy when compared to other classifiers, particularly SVM and k-NN. The classification of the quality and other dangerous components present in the treated water from the sewage treatment plants is made much easier by the application of machine learning techniques.

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