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Retraction

Retracted: An Intelligent Carbon-Based Prediction of Wastewater Treatment Plants Using Machine Learning Algorithms

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] A. M. Hilal, M. M. Althobaiti, T. A. E. Eisa et al., "An Intelligent Carbon-Based Prediction of Wastewater Treatment Plants Using Machine Learning Algorithms," *Adsorption Science & Technology*, vol. 2022, Article ID 8448489, 9 pages, 2022.

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Research Article

An Intelligent Carbon-Based Prediction of Wastewater Treatment Plants Using Machine Learning Algorithms

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Purification of polluted water and return back to the agriculture field is the wastewater treatment for plants. Contaminated water causes illness and health emergencies of public. Also, health risk due release of toxic contaminants brings problem to all living beings. At present, sensors are used in waste water treatment and transfer data via internet of things (IoT). Prediction of wastewater quality content which is presence of total nitrogen (T-N) and total phosphorous (T-P) elements, chemical oxygen demand (COD), biochemical demand (BOD), and total suspended solids (TSS) is associated with eutrophication that should be prevented. This may leads to algal bloom and spoils aquatic life which is consumed by human. The presence of nitrogen and phosphorous elements is in the content of wastewater, and these elements are associated with eutrophication which should be prevented. Adsorption of T-N and T-P activated carbon was predictable as one of the most promising methods for wastewater treatment. Many research works have been done. The issues are inefficiency in the prediction of wastewater treatment. To overcome this issue, this paper proposed fusion of B-KNN with the ELM algorithm that is used. The accuracy of the BKNN-ELM algorithm in classification of water quality status produced the highest accuracy of the highest accuracy which is $K = 9$ and $k = 10$ with rate of accuracy which is 93.56%, and the lowest accuracy is $K = 1$ of 65.34%. Experiment evaluation shows that a total suspended solid predicted by proposed model is 91 with accuracy of 93%. The relative error rate of prediction is 12.03 which is lesser than existing models.

1. Introduction

The impact of human behavior on the society, climatic changes in the environment, wastage from domestic resources, and industrial wastage causes pollution in the environment. Purification of wastewater treatment plant needs to filter some influent indictors in the water. The adsorption of influent indicators is filtered by using activated carbon. The operation of wastewater treatment is a complicated one but it can stable the purification of wastewater. There are so many existing techniques are available, but it can produce high variation in the quantity and quality of wastage water and also inadequate level of pollutant maintenance [1].

Table 1: Survey on techniques used in wastewater treatment.

Author name	Technique used	Feature extracted
Shahnaz et.al (2020) [17]	Multivariate optimization adsorption associated with nanocellulose	Cr (VI), Co (III), and Cu (II)
Kumar et.al (2020) [18]	Acid-activated water caltrop for the removal of hexavalent chromium from simulated wastewater	Hexavalent chromium
T. Shahnaz et.al (2020) [19]	EDTA-complexed acacia auriculiformis biomass	Hexavalent chromium
Patra et.al (2020) [20]	Pongamia pinnata shells for adsorption from simulated wastewater	Hexavalent chromium
Y¨onten et.al (2020) [21]	A thermodynamic and kinetic approach to adsorption from aqueous solution using a low cost activated carbon	Methyl orange
El Maguana et.al (2019) [22]	Prickly pear seed cake for dye removal	Activated carbon
Yakout et.al (2019) [23]	Magnetic graphene oxide nanoadsorbent for fast recovery from aqueous solutions	Methylene
Hasan et.al (2019) [24]	Activated carbon composite and its testing for methyl orange removal	Activated carbon
El Maguana et.al (2018) [25]	Activated carbon from walnut cake using the fractional factorial design	Activated carbon
Aravind et.al (2021) [26]	Using morphological operator for activated carbon for dye removal	Activated carbon
Alshabib et.al (2021) [27]	Wastewater treatment using DFT in activated carbon	Methylene-blue
Wang et.al (2021) [28]	Adsorption of dyes on an activated carbon	Carbon
Zhu et.al (2021) [29]	Carbon-based materials adsorption	Tetracycline and sulfamethoxazole

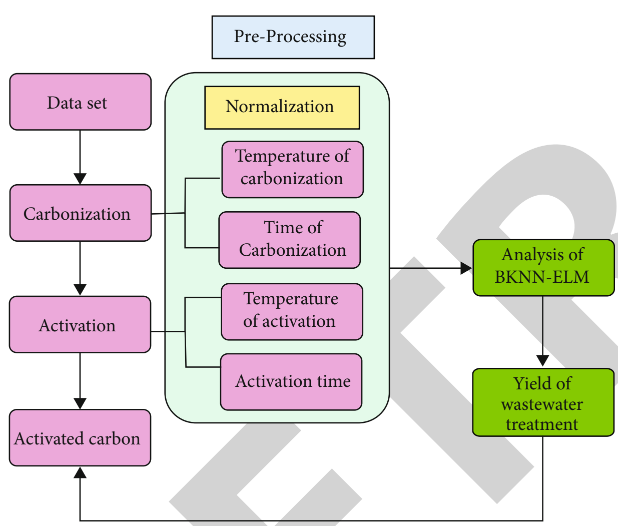

Figure 1: Architecture of BKNN-ELM.

To overcome these issues, this paper proposed fusion of BKNN-ELM predicting the influent indicators based on activated carbon and filtered out the unnecessary indicators in the wastewater treatment of plants. Also, it maintains the adequate level of minimum pollutant particles in the wastewater. The carbon presence in the water may damage the health and land usage. It is necessary to identify carbon presence before usage. The safe filtered technique can be used for accurate prediction. This research focuses on introducing carbon prediction technique with machine learning algorithms and sensors.

The biological process of WWTP called as ASP (activated sludge process) which is used to remove the pollutants like nitrogen, phosphorous, and biochemical demands from the stream of wastewater [2]. The prediction of wastewater quality is based on the key indicators of TSS, TN, TP, COD, and BOD using nitrogen-based carbon doped ammonia sensor. This separates from the sewage system using mathematical model as well as physical model that was developed [3], to improve the quality and quantity of wastewater treatment based on the conditions of the meteorological process. Therefore, it needs machine learning or deep learning techniques to process it. And also, total nitrogen (TN), total phosphorus (TP), and total suspended solids (TSS) were influent indictors for the wastewater treatment that uses ARIMA-based model and ANN [4, 5]. This paper [6] stated various techniques like random forests (RF), support vector machines (SVM), and multivariate adaptive regression splines (MARS) for predicting wastewater treatment. The prediction of influent indicators of wastewater employed the KNN technique [7]. Addition to that is that some hybrid techniques like classification and regressions were used [8]. The main contribution of this work is as follows:

(1) To present a framework for predicting the wastewater treatment based on influent indicators

(2) To analysis the BKNN-ELM under various performances of metric measures like precision, recall, sensitivity, effectiveness, prediction of probability rate, and accuracy

The paper has been organized as follows: Section 2 describes about the review of the literature, Section 3 introduces prediction of wastewater treatment using BKNN-ELM, Section 4 discusses about the experimented results, and Section 5 concludes the paper with future directions.

2. Review of Literature

In recent years, protection of the environment plays a vital role for human being to survive in the globe. The environment is polluted by the wastewater collected from the industrial wastage and domestic purpose wastage. The wastewater treatment has been carried out in the different influent

Step 1: for each parameter **do**
Step 2: if *class label* ∈ *training dataset* **then**
Step 3: *class dataset* ⟵ *class*
Step 4: Else
Step 5: *class type* ⟵ *class label*
Step 6: *class dataset* ⟵ *class*
Step 7: Endif
Step 8: end for

Algorithm 1: Separation of class using attributes.

Step 1: Procedure Find_Max()
Step 2: for each *class* in class dataset **do**
Step 3: If *class* > *maxinst* **then**
Step 4: *maxinst* ⟵ *class*
Step 5: endif
Step 6: end for
Step 7: *cmdaxpt* ⟵ *maxiiclass*
Step 8: *boundset* ⟵ [*class* ∈ *maxiiclass*]
Step 9: end procedure

Algorithm 2: Finding maximum and boundary set values.

Step 1: Procedure Find_Max()
Step 2: for each*class* in class dataset **do**
Step 3: If*class* < *maxinst***then**
Step 4:*maxinst* ⟵ *class*
Step 5: endif
Step 6: end for
Step 7: *cmdaxpt* ⟵ *maxiiclass*
Step 8: *boundset* ⟵ [*class* ∈ *maxiiclass*]
Step 9: end procedure

Algorithm 3: Finding minimum and boundary set values.

indicators to protect our environment. Therefore, wastewater treatment plants purify the polluted water and keep our environment clean and returned back our environment properly for the surveying of the human being. Activated carbon is an adsorption characterized and its structure format of porous, thermostability used in various applications like the removal of impurities, odor from medical usage, gaseous phases, and purifying the wastewater treatment [9]. Through activated carbon, the removal of dyes from the wastewater needs absorbing various pollutant particles at low cost and fast adsorption technique [10, 11].

Various machine learning algorithms like neural networks, SVM, and tree-based techniques were employed in the activated carbon-based prediction of WWTP [12–14]. This [15] paper proposed various ML algorithms such as support vector regression (SVR), linear regression (LR), and random forest regression (RFR) for predicting the activated carbon-based methylene blue number and iodine number. For predicting the dye adsorption in wastewater-based agrowastage in activated carbon, attributes like pH, surface area, and pore volume were employed. For that, the ML technique is implemented and improving prediction of impurities in an efficient way. Also, it provides the removal of agrowastage in the contaminated of wastewater treatment for the dyes particle in the water containment [16]. Table 1 shows survey on wastewater treatment's various techniques.

3. Proposed BKNN with ELM Methodology

Nowadays, industrial wastage pollutes the soil and affects the environment which has been adsorption by activated carbon. The wastage from industries which contains chemicals, soluble, and insoluble content is considered as solid wastage pollution. In this proposed work, we implement the fusion of BKNN with the ELM algorithm to improve the efficiency in the prediction of wastewater treatment plants. The architecture of proposed work (BKNN-ELM) is given in Figure 1.

Figure 1 describes three phases, namely, data collection, preprocessing, and analysis of BKNN-ELM.

3.1. Data Collection. In this work, data are collected from the waste water treatment plant (WWTP) in Busan, Korea, for three years from January 2008 to December 2010 [7]: total nitrogen (T-N) and total phosphorous (T-P) elements, chemical oxygen demand (COD), and biochemical demand (BCD).

3.2. Preprocessing. In the preprocessing, normalization process is done. The activate carbon has superior properties to eliminate the unwanted content in the WWTP.

3.2.1. Analysis of BKNN-ELM. In the BKNN technique, the bobbery set *k*-nearest neighbor (k-NN) method was used to predict the WWTP. It contains the parameters of total nitrogen (T-N) and total phosphorous (T-P) elements, chemical oxygen demand (COD), and biochemical demand (BCD). In the BKNN algorithm, the components in the training dataset are called as attributes. To create a class, same attributes values are considered as a group. The boundary value of the group in a class is defined by using maximum and minimum points in a class.

(1) BKNN. Algorithm 1 shows BKNN defining the classes using attributes and stored it into the form of lists.

Algorithm 1 describes grouping of classes based on the values of same attributes and storing attributes into lists. For each value in the class, B-*k*-NN defines its MMP minimum and maximum point value and BS (boundary set) which are used to predict the same class value of a testing input element. Algorithm 2 describes for each class. -*k*-NN finds the maximum and minimum points along with boundary set values that are analyzed.

Algorithms 2 and 3 describe that in order to improve the efficiency in the prediction of WWPT using the selection of the subset of data from the testing element, Algorithm 4 explains the fusion of BKNN with ELM.

(2) ELM (Extreme Learning Machine). ELM is the efficient and effective algorithm for predicting the wastewater

Step 1: Training the dataset(x_j, t_j) with input parameter values.
Step 2: Randomly choose the parameters of wastewater in the hidden layer
$$(a_j, b_j)\ j = 1, 2, \cdots n$$
Step 3: Evaluate the output matrix elements of hidden layer Hid
$$\text{out}^{(t)}(Hid) = p(Hid \mid x_j, \theta^{(t)})$$
Step 4: Evaluate the output weight $\beta = \text{out}^{(t)}(Hid) \mid (x_j, t_j)$

Algorithm 4: ELM.

Step 1: For prediction of WWTP in BKNN-ELM, implement 3.1.3.1 and 3.1.3.2.
Step 2: By using data set classify the class and grouping the subset of each class using same parametric values.
Step 3: Compute distance between each value in the class with its neighbors.
Step 4: Implement Algorithm 1 for classifying class with parametric values
Step 5: Finding the boundary values of minimum and maximum range using Algorithms 2 and 3.
Step 6: If two subsets are overlapped, minimized the boundary values of minimum and maximum range of values.
Step 7: Randomly choose subset group from the class, and it falls outside the boundary values of minimum and maximum range values that use algorithm 4 for prediction.

Algorithm 5: Prediction and evaluation BKNN-ELM (proposed).

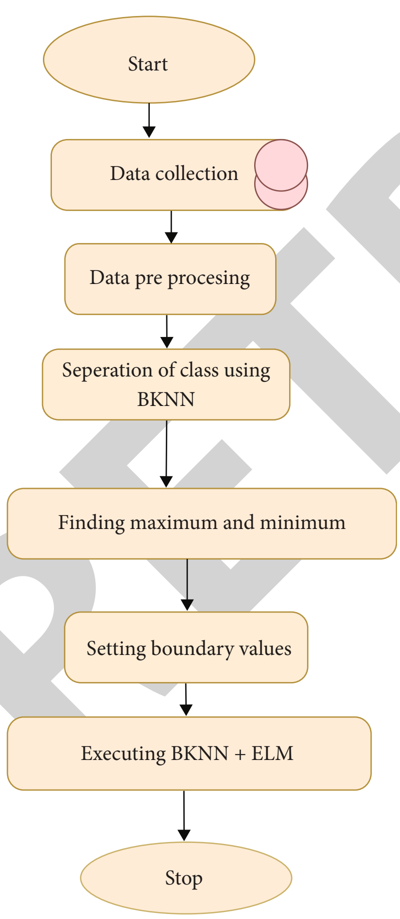

Figure 2: Flow chart of proposed work.

treatment based on activated carbon. The input vector values are mapped with high dimensional feature space. To classify the quality of water, extreme learning machine

Table 2: Selection of parametric values.

Influent parameters	Effluent parameters
Influent COD	Effluent COD
Influent pH	Effluent EC
Influent N	Effluent pH
Influent flow	Effluent N
Influent PO4	Effluent SO4
Influent EC	Effluent PO4

Table 3: Range of values of parameters describing influent wastewater.

Parameters	Minimum	Maximum	Average
T-N, mg/dm^3	19.8	99	70.4
T-P, mg/dm^3	3.8	38.6	13.55
BOD, mg/dm^3	40.5	792	378
COD, mg/dm^3	169	2520	930.1
TSS, mg/dm^3	82	1145	440
Q, mg/dm^3	26983	66883	38758

(ELM) is defined as

$$\text{out}_j = \sum_{i=1}^{n} \beta_i f n_i(x_j) = \sum_{i=1}^{n} \beta_i f n_i(x_j, a_i, b_i), \quad (1)$$

where out_j is the output vector values, and sample input values are $x_j.a_i, b_i$ which are learning parameter.

Algorithm 4 describes that training the new class in the dataset by adjusting the weight and bias value of the hidden

Table 4: Parametric values of MAE, MAPE, and R using fusion of BKNN-ELM.

Influent indicators	BKNN			ELM			BKNN-ELM		
	MAE	MAPE	R	MAE	MAPE	R	MAE	MAPE	R
T-N	6.08	9.54	0.56	7.07	12.54	0.46	4.18	7.54	0.36
T-P	1.71	13.87	0.58	2.71	18.87	0.56	1.55	11.67	0.48
BOD	45.12	14.39	0.62	48.12	14.91	0.66	40.12	13.39	0.42
COD	119.34	13.09	0.55	139.34	16.09	0.59	109.34	11.09	0.42
TSS	58.05	16.03	0.58	78.05	26.03	0.48	48.05	12.03	0.43

Table 5: Metric measure report.

Parameter	BKNN	ELM	BKNN-ELM
TP	132	170	120
TN	123	138	60
FP	65	35	20
FN	70	40	25
Accuracy	0.88	0.79	0.96
Precision	0.78	0.90	0.94
Recall	0.72	0.90	0.93

nodes in the layer. These are randomly choosing the input parameter values and produced the output. This ELM algorithm requires low computation time.

(3) BKNN-ELM (Proposed). BKNN-ELM enhances the accuracy and efficiency in terms of classification of the wastewater quality and reducing the computation time for both training and testing data set. Procedure for BKNN-ELM is given below:

Algorithm 5 describes the prediction process. It starts with training the process with BKNN with boundary set values of the training dataset. Then, it is implemented to the ELM procedure with testing data. If the testing data get falls within the range mentioned in the ELM, then this subset is added to the prediction list. Otherwise, it will be discarded from the training data set.

Flow chart is explained in Figure 2. The data is collected by analyzing various water points. Water contaminant contains toxic particles which are filtered using the proposed BKNN+ELM technique. The threshold level of minimum and maximum is set to extract the toxic data from dataset. Output is processed using BKNN+ELM.

4. Result Analysis

In this work BKNN-ELM, analysis is based on data collection from 3.1 and python to predict the wastewater quality using BKNN, ELM, and fusion of BKNN-ELM with parametric values. The parameters which are used in the WWTP are shown in Figure 2. To predict the water quality classification, accuracy, specificity, sensitivity, precision, and *F*-score, evaluation matrices were employed.

Accuracy defines how well the prediction data is true actually. Recall is considered as the ratio which is correctly predicted for positive values. Precision states true positive values out of overall positive prediction.

$$\begin{aligned} \text{accuracy} &= \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \\ \text{precision} &= \frac{\text{TP}}{\text{TP} + \text{FP}}, \\ \text{recall} &= \frac{\text{TP}}{\text{TP} + \text{FN}}, \\ \text{F1} - \text{Score} &= \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}. \end{aligned} \tag{2}$$

Table 2 shows the parameter selection. In the WWTP, these parameters are used to predict the parametric values in the dataset.

Table 3 shows the influent parameter values of wastewater quantity and quality, and the ranges of variation were established [1]. The parametric values in Table 3 indicate substantial variation in T-N, T-P, BOD, COD, TSS, and Q values. These indicators of wastewater quality constitute input data for the models of BKNN-ELM describing the changes in carbon, nitrogen, phosphorus, and biochemical changes in the compounds of bioreactors.

By using the Table 3, parametric values our proposed work BKNN-ELM predicting activated carbon-based T-N, T-P, BOD, COD, and TSS values using mean absolute error (MAE), mean relative error (MAPE), and coefficient of correlation (R). The analysis of these parameters is shown in Table 4.

The analysis of Table 4 shows that T-N prediction activated carbon-based on BKNN in MAE = 6.08 mg/dm^3 and ELM in MAE = 7.07 mg/dm^3, and fusion of BKNN-ELM gives MAE = 4.18 mg/dm^3, similarly for MAPE and BKNN in MAPE = 9.54 mg/dm^3 and ELM in MAPE = 12.54 mg/dm^3, and fusion of BKNN-ELM gives MAPE = 7.54 mg/dm^3. In addition, T-P prediction activated carbon based on BKNN in MAE = 1.71 mg/dm^3 and ELM in MAE = 2.71 mg/dm^3, and fusion of BKNN-ELM gives MAE = 1.55 mg/dm^3, similarly for MAPE and BKNN in MAPE = 13.87 mg/dm^3, ELM in MAPE = 18.87 mg/dm^3, and fusion of BKNN-ELM gives MAPE = 11.67 mg/dm^3. Prediction of wastewater quality by parametric indicators of T-N and T-P shows that our proposed work BKNN-ELM gives better performance. Similarly, other indicators of BOD, COD, and TSS also show that the lowest prediction errors were

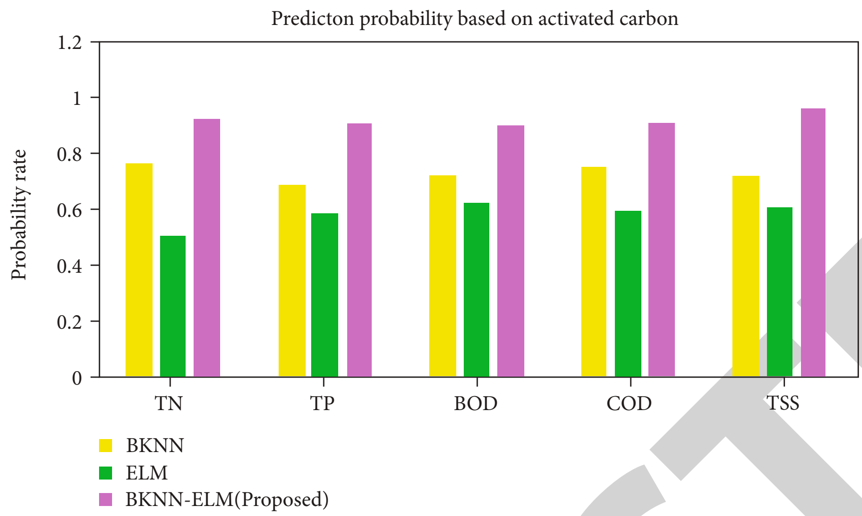

Figure 3: Prediction of influent indicators.

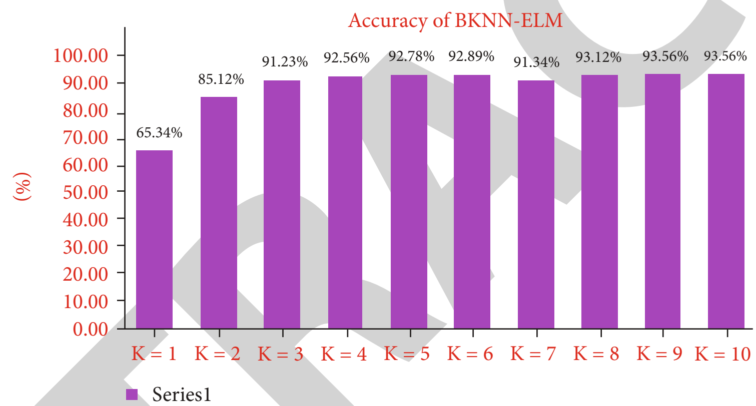

Figure 4: Accuracy rate of k in BKNN-ELM.

Table 6: Effectiveness.

Algorithms	Effectiveness				
	TN	TP	BOD	COD	TSS
BKNN	65	55	66	54	66
ELM	45	34	40	49	72
BKNN-ELM	92	82	93	94	91

observed for the BKNN-ELM approach. Table 5 shows the report of performance metric measures.

From the above Table 5, the accuracy of BKNN-ELM (proposed work) is higher as compared to other classifier algorithms of BKNN and ELM. In Table 5, the next higher accuracy is ELM which is also closer to BKNN-ELM. Figure 2 shows the prediction of wastewater treatment for plants based on activated carbon prediction of parametric indicators of TN, TP, BOD, COD, and TSS along with different machine learning algorithms like BKNN, ELM, and fusion of BKNN with ELM.

From Figure 3, it seems that our proposed work BKNN-ELM gives the better probability prediction of wastewater treatment for plants. Figure 4 shows the accuracy rate for implementation BKNN-ELM with various K values.

Figure 4 shows that value of K has the highest accuracy which is $K = 9$ and $k = 10$ with rate of accuracy that is 93.56%, and the lowest accuracy is $K = 1$ of 65.34%. Table 6 shows the effectiveness of various machine learning algorithms in terms of various influent indicators by using

$$\text{Effectiveness} = \frac{N - L}{N} \times 100, \tag{3}$$

where N is the total number of testing data, and L is the total number of losing test data.

From Table 6, it seems that effectiveness of our proposed work produces better result compared it with other existing algorithms. Figure 4 shows the computation time of BKNN, ELM, and fusion of BKNN with ELM using various influent indicators.

Figure 5 seems that our proposed work gives less computation time to predict the wastewater treatment of plants using various influent indicators. Figure 6 shows the

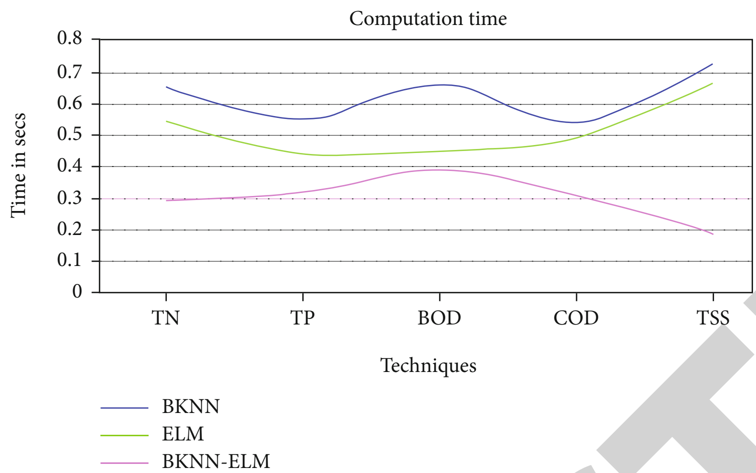

Figure 5: Computation time.

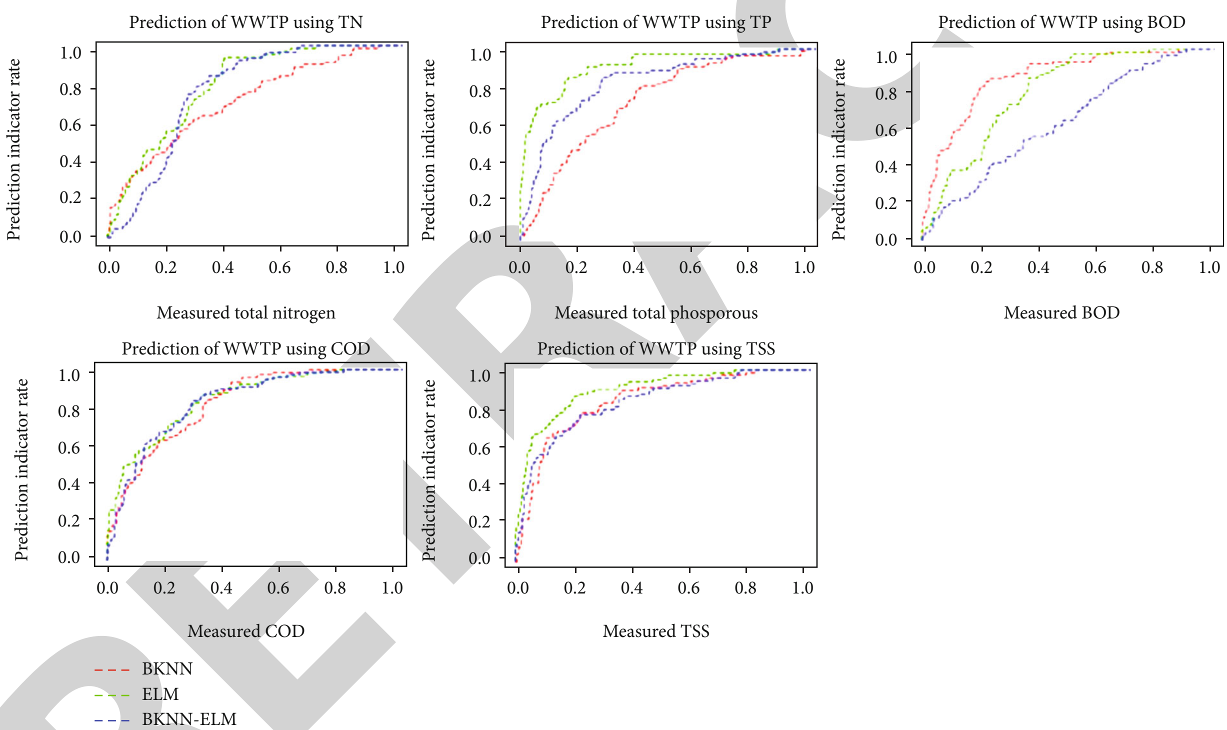

Figure 6: Statistical analysis of prediction of various indicators.

BKNN-ELM model for predicting the influent water based on activated carbon with various indicators.

Figure 6 seems that our proposed work gives effective prediction of WWTP measured various indicators for the treatment of plants.

5. Conclusion

The prediction of wastewater treatment plants uses adsorption of unwanted influent indicators using activated carbon. In this work, BKNN-ELM uses predicting the influent indicators in the wastewater and identifying the maximum and minimum point value with boundary set values. It also implemented various parameters like total phosphorous (T-P), total nitrogen (T-N), BOD, COD, and TSS. BKNN-ELM accurately predicting the unwanted influent indictors and filtered it using activated carbon with minimum error prediction and also proving the efficient and robust performance. The accuracy of BKNN-ELM algorithm in classification of water quality status produced the highest accuracy of the highest accuracy which is $K = 9$ and $k = 10$ with rate of accuracy that is 93.56%, and the lowest accuracy is $K = 1$ of 65.34%. Our proposed work BKNN-ELM outperforms the best result compared it with existing classifier. The limitation of the study is that the prediction is done only for T-P, T-N, and oxygen demand. Further future research must need sensors for predicting actual carbon particles. In future work, this will be extended by using various ML algorithms and also upgrade our work in various influent and effluent indicators for predicting the wastewater treatment for plants.

Data Availability

All the required data is available in the article itself.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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