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A STUDY ON THE RELIABILITY OF AN ARTIFICIAL INTELLIGENCE MODEL FOR WATER ENVIRONMENT EVALUATION

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ABSTRACT: The objective of this study is to discover the most effective water environment improvement measures for the 109 most important watersheds of Japan, which are well-known Class-A watersheds under the jurisdiction of the Japanese government. An artificial intelligence (AI) model has been created by applying Deep Learning technologies with the expectation that an AI model is able to take adevantage of the multiple categorical water environmental data, and watershed information from 109 watersheds has been collected as teacher data to train the AI model. This study aims to find the best way to present the water environment data to an artificial intelligence model. To provide the most reliable water quality estimations, three different ways of water environment data presentation have been examined. It has been identified that presenting the raw environment data to the AI model as teacher data is the best way for building an AI model. This study concludes by pointing out that preprocessing data will cause information loss of teacher data and will also add biased information to teacher data. Therefore, using raw data without preprocessing as teacher data will help build a more reliable AI model. It is hoped that this study will contribute to establishing a more reliable river environment planning and management methodology.

Keywords: Water Environment, Artificial Intelligence (AI) Model, Teacher Data, Data Preprocessing

1. INTRODUCTION

A fundamental quetion in water environment evaluation and planning is how to take into consideration of environmental information and experiences as much as possible. The recent researches[1] have shown that an Artificial Intelligence model is a powerful tool to provide a better answer to the above question.

Water environment evaluation and planning historically have been dependent on 1) mathematic models that simulate all the physical, chemical, and biochemical processes leading to water environment changes over time and space, and 2) the expertise of planners on a specific river [1-3]. Mathematic models connect all direct water environment factors to management goals, and the final evaluation and decision-making are usually based on the expertise of planners. In this planning process, most of the indirect environmental factors have not been taken into consideration in a reasonable and proper manner, and expertise tends to put much more weight on the characteristics of a specific river and ignore the common characteristics of all the other rivers in the same region. How to evaluate and apply the experiences and lessons all rivers with some common characteristics can provide is a question that remains unanswered.

This study approaches this problem by applying the water environment big data to environment planning with the help of an Artificial Intelligence (AI) model. AI model has been widely applied to water environment evaluation and planning [4-8]. The reason why an AI model has been chosen is its powerful capability of processing various types of water environment data such as numerical data, categorical data, and image data. It does not require any specific categorizations while presetting data to an AI model [4,5].

This powerful capability of AI models, however, has raised a critical question: as the teacher data required for AI model training, what is the best way to present water environment data to an AI model? A typical water quality index BOD (Biochemical Oxygen Demand) usually can be recorded and represented at least in three different ways: 1) BOD is mostly mentioned in the raw numerical data form that has the unit mg/l; 2) BOD is also quite frequently represented by its class according to the water Environment Quality Standards (EQSs) such as Class AA, Class A, etc.; 3) BOD is the categorical yes/no answer to the question whether the administrational water environment management goal has been achieved. The numerical raw data form is the most basic form of BOD data, and the other two forms are the preprocessed results. The most common preprocessing includes filtering and converting, and both EQSs and administrational water environment management goals are served here as a filter. An AI model is capable of dealing with each form of water environment data with or without preprocessing mentioned above.

The ultimate goal of this study is to find the best way to present water environment data to an AI model for the purpose to create a more reliable water environment evaluation AI model, and finally to establish a general procedure for AI model application to water environment evaluation.

2. RESEARCH SIGNIFICANCE

This study seeks to develop a reliable procedure to construct an Artificial Intelligence model for water environment evaluation. Three different ways of teacher data presentation have been examined, and the water quality estimation results provided by the well-trained AI model have been compared with water quality observation results to identify what kind of teacher data helps build a better AI model in terms of the accuracy of water quality estimation. We have successfully identified the raw data as the best way of teacher data presentation and reached a reasonable conclusion that any unnecessary preprocessing of big data only for human conveniences or computational purposes will damage the reliability of teacher data.

3. ARTIFICIAL INTELLIGENCE MODEL

An artificial intelligence model, specifically a neural network model has been adopted to compose a water environment evaluation method for evaluation or prediction problems due to the suitability of neural network models [5-9].

3.1 Structure of Neural Network [5]

A neural network is a network system constructed artificially by idealizing the neurons (nerve cells) and consists of a number of nodes and lines that are called units and connections (or links) respectively. Based on the differences in network structures, neural networks generally are classified into two types: layered networks and interconnected networks. It has been shown that a layered network is suitable for evaluation/prediction problems due to its abilities in learning (self-organization) and parallel processing of information.

A typical layered neural network has a layer of input units at the top, a layer of output units at the bottom, and many hidden layers between the input layer and the output layer. Connections exist only between the units in the adjacent layers and connections within a layer or from higher to lower layers are forbidden.

3.2 Modelling A Neural Network

For the sake of simplicity, a neural network can be considered as a unit consisting of three layers: let the unit numbers of the input layer, hidden layer, and output layer be N, M, and 1, respectively. When an input $\{I_i,\ i = 1,2,\cdots,\ N\}$ is given to the units of the input layer, the inputs and outputs of the hidden layer units as well as the output layer units are represented as follows.

$$Y_j = f\left(X_j\right),\ \ j = 1,2,\cdots,M \tag{1}$$

$$X_j = \sum_{i=1}^{N} w_{ij} I_i + \theta_i \quad , \quad j = 1,2,\cdots,M \tag{2}$$

$$O = f(Z) \tag{3}$$

$$Z = \sum_{j=1}^{M} w_j Y_j + \theta \tag{4}$$

Where Y_j : output from the unit j of the hidden layer.

X_j : input the unit j of the hidden layer.

$f(\cdot)$: unit output function.

w_{ij}: connection weight between the input layer unit i and hidden layer unit j.

θ_j : threshold value of the hidden layer unit j

O : output from the output layer unit.

Z : input to the output layer unit.

w_j: connection weight between the hidden layer unit j and the output layer unit.

Θ : threshold value of the hidden layer unit j

For the unit output function $f(\cdot)$, some expressions have been proposed. The following Sigmoid function has been applied frequently. However, it is not necessarily the best one in terms of learning efficiency. A testing process for different output functions is strongly suggested. In this study, this Sigmoid function has been finally adopted after careful tests.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

Theoretically, the neural network model expressed by Eqs. (1) through (5) is able to approximate any non-linear relationship between inputs and outputs with any degree of accuracy by using enough hidden layer units and setting connection weights and thresholds to be appropriate through proper learning processes [9]. The potential of this model has been verified with similar problem to this study [4-7].

3.3 Learning Process of Neural Network Model

or a neural network model, the process of setting the connection weights unit thresholds is called *learning*. The term *learning* here means the self-organization process through which the neural network model automatically adjusts all the parameters (i.e. all the connections and thresholds) to the appropriate values when a series of samples of input-output data (called teacher data or teacher signals) are shown to the model. If we consider the information processing in a neural network model as a transformation of input data to output data, then model learning can be considered to be a process through which the neural network model gradually becomes capable of imitating the transforming patterns represented by the teacher data.

A lot of learning algorithms have been proposed, and among them, the Error Back Propagation Algorithm is the most widely used and most successful. The following is the summary of the Error Back Propagation Algorithm [11].

Suppose T sets of teacher data are given.

$$\left\{I_1^{(t)}, I_2^{(t)}, \cdots, I_N^{(t)}, O^{(t)};\ t = 1,2,\cdots,T\right\} \tag{6}$$

Notice that the teacher data consists of two parts: the input part $\left\{I_1^{(t)},\ I_2^{(t)}, \cdots,\ I_N^{(t)};\ t\ = 1, 2, \cdots, T\right\}$ and the output part $\left\{O^{(t)};\ t = 1,2,\cdots,T\right\}$.

Now consider an initial value

$$w_{ij}^{[k]}, w_j^{[k]}, \theta_j^{[k]}, \theta^{[k]}\ \ , k = 0 \tag{7}$$

for each of the connection weights and threshold values, respectively. Notice that the superscript [k] indicates the number of learning iterations and [k=0] means the initial values for all the parameters directly preceding the start of the learning process. Then the outputs corresponding to the inputs of the teacher data $\left\{I_1^{(t)},\ I_2^{(t)}, \cdots,\ I_N^{(t)};\ t\ = 1, 2,\ \cdots,\ T\right\}$ can be obtained from Eq. (1) ~ Eq. (5). Let these outputs be $\left\{U^{[k](t)};\ t = 1, 2, \cdots,\ T\ and\ k = 0\right\}$. Clearly, $\left\{U^{[k](t)};\ t = 1, 2, \cdots,\ T\ and\ k = 0\right\}$ are different from the outputs of the teacher data $\left\{O^{(t)};\ t = 1,2,\cdots,T\right\}$, and an error function can be defined with the two different kinds of outputs as follows.

$$R^{[k]} = \sum_{t=1}^{T}\left(O^{(t)} - U^{[k](t)}\right)^2,\ \ k = 0 \tag{8}$$

Obviously, $R^{[k]}$ is a function of connection weights and threshold values because $\left\{U^{[k](t)};\ t = 1, 2, \cdots,\ T\ and\ k = 0\right\}$ are calculated after all $w_{ij}^{[k]}$, $w_j^{[k]}, \theta_j^{[k]}\ and\ \theta^{[k]}$ are given.

The Error Back Propagation Algorithm makes use of the connection weights and threshold values that minimize the above error function $R^{[k]}$. Usually, a non-linear programming method is required to solve the optimization problem along with an iteration process in order to obtain the optimal (but possibly suboptimal) connection weights and threshold values. The final iteration procedures derived from a non-linear programming method known as the Method of Gradient Descent are as follows.

$$w_j^{[k+1]} = w_j^{[k]} - \eta \cdot \sum_{t=1}^{T}\left(\delta^{[k](t)} \cdot Y_j^{[k](t)}\right) \tag{9}$$

$$\theta^{[k+1]} = \theta^{[k]} - \eta \cdot \sum_{t=1}^{T}\delta^{[k](t)} \tag{10}$$

$$w_{ij}^{[k+1]} = w_{ij}^{[k]} - \eta \cdot \sum_{t=1}^{T}\left(\delta^{[k](t)} \cdot w_j^{[k+1]} \cdot \gamma_j^{[k](t)} \cdot I_i^{(t)}\right) \tag{11}$$

$$\theta_j^{[k+1]} = \theta_j^{[k]} - \eta \cdot \sum_{t=1}^{T}\left(\delta^{[k](t)} \cdot w_j^{[k+1]} \cdot \gamma_j^{[k](t)}\right) \tag{12}$$

where the superscript [k] indicates the number of learning iterations as mentioned earlier, and η is a small positive number that indicates the step size of the Method of Gradient Descent for the optimization iteration process. The other variables which occurred in the final learning procedures are defined as follows.

$$\delta^{[k](t)} = (O^{(t)} - U^{[k](t)}) \cdot O^{(t)} \cdot (1 - O^{(t)}) \tag{13}$$

$$\gamma_j^{[k](t)} = Y_j^{[k](t)} \cdot \left(1 - Y_j^{[k](t)}\right) \tag{14}$$

In order to avoid the overfitting (or over-learning) problem, a criterion is usually required to make a judgment when the iterative learning process should be terminated. In this study, the learning process will be stopped when the Mean Relative Error (MRE) of the outputs is less than a specified relative error expectation for prediction/evaluation results, which is a common treatment for a learning process of teacher data with random errors (i.e. white noise). Needless to say, this error expectation should be set according to the required accuracy of the problem which is being dealt with.

4. WATER ENVIRONMENT DATA

An artificial intelligence model is a set of mathematical procedures that are designed to process the so-called big data, and an application of artificial intelligence models requires collecting big data, presenting big data to the AI model, and training the AI model with big data. The following is the detail of this process.

4.1 Teacher Data

In order to apply the neural network model proposed above to a water environment evaluation problem, the model has to be trained appropriately through a deep learning process by using water-environment-related data.

In this study, the data obtained from the water quality survey conducted for the 109 Class-A rivers of Japan are used for the deep learning process [12]. The data are stored in an open-source database that is maintained by the Ministry of Land, Infrastructure, Transport and Tourism of Japan.

After a careful data verification process, only 104 rivers out of 109 Class-A rivers are chosen to be included in the teacher data set for deep learning because quite a few data are missing for the other 5 rivers. For each river, the data includes 58 water

Table 1 Water environment items of teacher data

Category (Number of Items)	Water Environment Item	
Time of Sampling (4)	Year Day	Month Hour
River/Flow Conditions (17)	Place of Sampling Water Level Total Water Depth Sampling Temperature Vertical Visibility Water Smell Time of Low Tide of Sampling Day Time of High Tide of Sampling Day Visual Appearance: Water Color Turbidity (Muddiness) Waste/Garbage	Weather Quantity of Flow Water Depth of Water Temperature Horizontal Visibility Flow Strength Floating
Watershed Conditions (7)	Length of Main Stream Catchment Population Tributaries Annual Average Stream Flow Number of Hydraulic Power Plants	Catchment Area Number of Number of Dams
Water Quality Indexes For The Living Environment (10)	pH COD DO of DO Total Coliform The Amount of N-Hexane Extract (Oil) Total Nitrogen	BOD SS Saturation Degree Total Phosphorus
Water Quality Indexes About Human Health (9)	Cadmium Lead Chromium Arsenic Alkyl Mercury Dichloromethane	Cyanogen Hexavalent Total Mercury PCB
Water Quality Index For Inflow Of Domestic Wastewater (1)	Ammonium Nitrogen	
Others (10)	Chromaticity Evaporation Residues Potassium Permanganate Consumption Sodium Manganese Residual Chlorine	Turbidity Total Hardness Iron Aluminum
(7 categories in total)	(58 items in total)	

Table 2 Water environment quality standards for rivers [13]

Item Class	Water Use	Standard Value				
		Hydrogen-ion Concentration (pH)	Biochemical Oxygen Demand (BOD)	Suspended Solids (SS)	Dissolved Oxygen (DO)	Total Coliform
AA	Water supply class 1, conservation of natural environment and uses listed in A-E	6.5≤pH≤8.5	≤1 ㎎/L	≤25 ㎎/L	≥7.5 ㎎/L	≤50MPN/100mL
A	Water supply class 2, fishery class 1, bathing and uses listed in B-E	6.5≤pH≤8.5	≤2 ㎎/L	≤25 ㎎/L	≥7.5 ㎎/L	≤1000MPN/100mL
B	Water supply class 3, fishery class 2, and uses listed in C-E	6.5≤pH≤8.5	≤3 ㎎/L	≤25 ㎎/L	≥5.0 ㎎/L	≤5000MPN/100mL
C	Fishery class 3, industrial water class 1, and uses listed in D-E	6.5≤pH≤8.5	≤5 ㎎/L	≤50 ㎎/L	≥5.0 ㎎/L	-
D	Industrial water class 2, agriculture water, and uses listed in E	6.0≤pH≤8.5	≤8 ㎎/L	≤100 ㎎/L	≥2.0 ㎎/L	-
E	Industrial water class 3 and conservation of environment	6.0≤pH≤8.5	≤10 ㎎/L	Floating matter such as garbage should not been observed	≥2.0 ㎎/L	-

environment items as shown in Table 1. The data records used in this study are from 1998 to 2018 with a duration of 21 years long.

The 58 environment items are divided into two parts to form a teacher data set, evaluation goal variables, and explanatory variables. The evaluation goal variables include the five environment items that are used to define The Water Environment Standards for Rivers as shown in Table 2 [13], which are pH, BOD, SS, DO, and Total coliform. The five environment items are used to explain how the achievement degree of water Environment Quality Standards is impacted.

4.2 Presenting the Teacher Data

In this study, the evaluation goal variables of the teacher data have been presented to the environment evaluation AI model in the following three different ways in order to identify the best way of teacher data presentation by comparison.

Firstly, as the most basic way, the raw data of water quality are directly presented to the AI model. The five environment items, pH, BOD, SS, DO, and Total Coliform are presented as continuous numerical raw data, without any preprocessing, to the AI model as teacher data.

The second way is to present the achievement degree of water Environment Quality Standards to the AI model instead of the raw water quality data. The achievement of EQDs has been scored with an effort to make the final scores for different standard classes that are corresponding to different water use purposes a uniform distribution, which is expected to maximize the score distance between different standard classes. The results are shown in Table 3.

The third way is to present the AI model with the categorical yes/no data on whether the administrational water environment management goal has been achieved for each water quality item.

Needless to say, the explanatory variables of the teacher data are presented as raw data without any pre-processing despite the very basic and reasonable question of whether this is the best way to present the explanatory variables to AL models is remained to be answered, which is beyond the research purpose of this study though.

Table 3 Scoring of achievement degree of EQSs

Water quality class ranked with EQSs for conservation of the living environment	Score
AA	0.9
A with indexes ranked in AA	0.8
A	0.7
B with indexes ranked in A or higher	0.6
B	0.5
C	0.4
D	0.3
E	0.2
Below E	0.1

4.3 Training Neural Network Model

As we explained previously, the neural network model has been trained (put under a learning process) with the collected teacher data. The training process is based on the learning procedures but it is still a process of trial and error because there are still many details that remain undecided, such as a suitable step size of optimization, a suitable output function, an efficient order to present the teacher data to the neural network model, and a proper initial network size (layers and units in each layer). The learning process was stopped after the trained neural network model is able to reproduce the entire teacher data with an acceptable error, which was set in this study to be below 2% in terms of mean relative error.

5. DATA PRESENTATION COMPARISON

In order to identify which of the three

presentation ways of the teacher data helps construct a better AI model, this study has compared the estimation results of administrational environment management goal achievement by the Al models with the observation results for the year 2019 (including four season results), which is right after the teacher data duration 1998-2018. The administrational environment management goal achievement has been chosen as the comparison item because it is a common output that three well-trained AI models can generate.

It is worth noticing that the administrational management goal model provides the management goal achievement directly while the other two models provide water environment estimation results that require a converting process to get the management goal achievement results. This might give the administrational management goal model some kind of advantages, which will be discussed in the next section.

5.1 Indexes for Comparison

There are many different standards and many different methods available for model comparison [14,15]. Tatehira [16] has shown that comparing the efficiency of taking advantage of the uncertainty value of future estimation/forecast is the most basic and reliable method of model comparison. The following three well-established statistical evaluation indexes for comparing the presentation ways of teacher data have been defined based on the comparison results of the AI model estimation and observation as shown in Table 4.

$$\text{Accuracy} = \frac{Hits(A)+Hits(U)}{Hits(A)+False(A)+False(U)+Hits(U)} \quad (15)$$

$$\text{Threat Score(A)} = \frac{Hits(A)}{Hits(A)+False(A)+False(U)} \quad (16)$$

$$\text{Threat Score(U)} = \frac{Hits(U)}{Hits(U)+False(A)+False(U)} \quad 17)$$

Table 4 Comparison of administrational management goal achievement results

Estimation Results by AI Model	Observation results	
	Achieved	Unachieved
Achieved	Hits(A)	False(A)
Unachieved	False(U)	Hits(U)

Accuracy is the most common and comprehensive index to compare different models. The threat Score is used to measure how well each model can hit the target (achieved or unachieved). Threat score(A) usually is used when the achievement rate is emphasized, and Thread Score(U) is used when the un-achievement rate is emphasized. All three indexes are defined between 0 to 1, and 1 means an ideal estimation.

5.2 Presenting the Teacher Data

As shown in Table 5, the three different data presentation ways have been compared based on the three indexes defined above for the year 2019, which is right after the teacher data duration.

Table 5 Estimation results of administrational management goal achievement during 2019

Way of data presentation	Accuracy	Threat Score (A)	Threat Score (U)
Raw data of water quality	96.88%	96.22%	84.71%
Water EQSs Class score	92.55%	90.96%	70.19%
Management goal achievement	97.12%	96.57%	84.62%

Table 5 demonstrates that scoring the teacher data according to the water achievement degree of EQSs generated the worst estimation results of the three different ways of teacher data presentation. A reasonable explanation for this result is that both the water EQSs and the scoring process are either subjective or arbitrary, which means they have been decided for human conveniences or computational purposes without any consideration of the water quality evolution processes. These possibly-biased human pre-processing added to the teacher data have damaged the reliability of the original raw teacher data as a logical hypothesis.

This hypothesis is also consistent with the fact that the AI model with the raw data as teacher data generated the best water quality estimation in terms of threat score (U). This is because the raw data without any pre-processing, just as expected, include all the original information about the hidden water quality natural evolution processes.

Also, the categorical teacher data of the administrational management goal achievements help the AI model generate even better water quality estimation results in terms of both accuracy and threat score(A) than the AI model trained with raw data does. The reasonable explanation is that the outputs of the AI model trained with the administrational management goal achievements are exactly the results that are used in comparison indexes. Because the differences in the comparison indexes between the two models are small enough to be ignored although the AI model trained with the raw data even has not been given any information on the administrational management goal achievements, it is reasonable and fair enough to justify the hypothesis that the AI model trained with the raw data model is more reliable than the other models trained with different teacher data in terms of producing accurate water quality estimations. Simply, raw data set without any preprocessing is the best teacher data set.

6. CONCLUSION

With the purpose to build a reliable artificial intelligence model for water environment evaluation and planning, this study examined different ways in which teacher data are presented to an AI model for its training process or learning.

Artificial intelligence models are so comprehensive and powerful that they are capable to deal with various kinds of teacher data such as numerical data, categorical data, image data, etc. Data pre-processing techniques allow model-builders to convert data types so that the well-trained AI model can serve the model builder's purpose better.

This study has examined three different water environment data types (or three different ways of teacher data presentation) as teacher data for AI model training, and water quality estimation results. In order to identify what kind of teacher data help build a better AI model in terms of accuracy of water quality estimation, the well-trained models have been compared with observation results.

The results have shown that the raw water quality data without any pre-processing generated a better AI model than the other two teacher data types with pre-processing. Furthermore, the teacher data preprocessed slightly with a simple criterion about whether the administrational environment management goals have been achieved, generated an even better final model than the heavily-preprocessed teacher data based on the complicated water EQSs for rivers.

Based on the above results, a hypothesis can be formed: preprocessing raw data will possibly cause information loss of the teacher data or add biased information into the teacher data, while raw data without preprocessing will serve as the best teacher data, and help build a more reliable AI model. Needless to say, this hypothesis remains to be further examined.

Moreover, this hypothesis does not deny any necessary teacher data preprocessing if the preprocessing serves the research purpose very well. For example, if the only purpose of building an AI model is to answer the question of whether the administrational water environment management goal will be achieved, preprocessing water quality data into categorical yes/no data still can provide an answer with an acceptable satisfaction degree.

Further research will focus on applications of the well-trained AI model, such as identifying the most influential water environment factors/items as well as the most effective water environment improvement measures for each river of the 104 Class-A rivers that contribute to the teacher data. These researches all together are expected to contribute to establishing a more reliable river environment planning and management methodology.

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