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Approach of Deep Learning Model Based Multi-Layer Feed-Forward Artificial Neural Network with Backpropagation Algorithm for Water Quality Prediction

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Abstract

Quality of water resources is crucial to several activities in human life and life under water. Water resource quality is a complex dynamic system depending on various attributes with nonlinear and non-equilibrium conditions. In this study, we aim to utilize a deep learning (DL) model based on multi-layer feed-forward artificial neural network with back-propagation algorithm and supervised data for water quality prediction. The DL model predicts the water quality from database information that collected by the Pollution Control Department (PCD), Thailand. The following water quality attributes from 2007–2019 were analyzed: biological oxygen demand (BOD), dissolved oxygen (DO), fecal coliform bacteria (FCB), total coliform bacteria (TCB), ammonia-nitrogen (NH_3-N), and spatial-temporal data for the Chao Phraya River in Thailand. The results indicated that the DL model had a coefficient of determination (R^2) of 0.90, with a mean square error (MSE) of 0.20 and a predicted accuracy of 88.96%. The evaluation DL model result was more precise in predicting values in the unsuitable and poor water quality classes, with 100% of the dataset being in those classes. The DL model was able to process the data at circa 18,000 rows per second. These results supported the possibility of using the DL model as a tool to predict the quality of water resources.

Keywords: Environmental and information analysis; Supervised data; Data prediction; River water-quality; Chao Phraya River

1. Introduction

The rapid expansion of urban communities and economic zones due to the growing population and the advancement of technology can affect to a crucial index of river water quality because the wastewater from various activities discharged of communities and industries, sewage and debris are drained into canals and rivers. Later, the waste decays and accumulates, leading to spoilage of the water (Loukas *et al.,* 2003; Marsili-Libelli *et al.,* 2003; Veesommai and Kiyoki, 2018; Ho *et al.,* 2019; Qian *et al.,* 2020; Kirschke *et al.,* 2020). This problem is the main cause of the destruction of the ecosystem in water bodies. So, river is a carrying wastewater source, at the same time they are sources for produced irrigation water that will be used in agriculture, domestic, industry, and the ecosystem. However, the quality of the river water itself is most important regarding human health, aquatic live, aquatic vegetation, and other aspects of ecosystems and human usage. Therefore, the quality of water river should be a concern and preventative measures taken to ensure its appropriate quality (Antonopoulos *et al.,*2001; Loukas *et al.,*2007).

The water quality monitoring process is carried out onsite using sensors, which can provide real-time data and sampling water can be analyzed in the laboratory.

However, the current situation of river may not adequately reflect the future situation. So that, several different computational methods based on statistics are widely applied to analyze and predict the future water quality in rivers. These methods require accurate sample analysis, much computing time, and involve a high operating cost for accurate sample analysis (El-Shafie *et al.,* 2012; Wang *et al.,* 2013; Khani *et al.,* 2017; Kim *et al.,* 2019; Tung *et al.,* 2020). Consequently, more precise data analysis models have been utilized including learning models such as decision trees, artificial neural networks etc. to analyze and predict data in many fields including economics, finance, and the environment (Muttamara and Sales, 1994).

Due to artificial neural networks (ANNs) limited within two-three layers of learning and few hidden layers, then it able to obtaine supervised data only in specific task and some are missing generalizable (Miotto *et al.,* 2018). Therefore, multiple layers learning is developed and namely "deep" learning (DL) (Zhu *et al.,* 2017). Deep learning (DL) is a subfield of machine learning and form by computational model for learning of the representing data. DL is trained dataset with algorithm with multiple layers to learn represented data pattern without any manual guideline, which is formed by the composition of multiple attributes, levels and processing layers. The composition within DL is can be design according to objective and task of model (Guo *et al.,* 2016; Miotto *et al.,* 2018). There are several types of DL such as Perceptron (P), Feed Forward (FF), Radial Basis Network (RBF), Deep Feed Forward (DFF), Recurrent Neural Network (RNN), Long/Short Term Memory (LSTM), Auto Encoder (AE), Denoising AE (DAE) Convolutional Neural Network (CNN), etc. The most simply structure type of DL model is Multi-layer Feed-forward Neural Network with Backpropagation (MAMFFN) because (i) the process will be started from input layer then forwards to the hidden layer gradually until output layer (one direction without loop) and (ii) the process is able to perform nonlinear and linear mathematical model of large data (Gajendran and Vasanthi, 2019). For training the multi-layers in MAMFFN process, the most used algorithm is Backpropagation (BP) algorithm, which is commonly trained neural network. BP algorithm is suitable for training non-linear relationship between input and output dataset by adjusting weight of each layers.

Currently, applying deep learning (DL) is rapidly becoming a useful tool for analysis, classification and prediction the data due to DL able to compute the multiple data layers, fast simulation to predict an output, minimize the massive tagged data in the training process (Gupta and Agrawal, 2019; Ma and Liu, 2020). Based on DL ability and data-driven method, researchers are wildly used for their complicated data and data sources like a Jang *et al.* (2021) applied DL which provided 85.0% of accuracy and prediction 71.7% for analysis the pCR or GR by using the post-chemoradiotherapy T2-weighted axial MR image compare with the observed results, Ayon and Islam (2019) were utilized DL to diabetes prediction in Bangladesh and the result shown the high accuracy at 97.11%. DL with MAMFFN and BP algorithm has a great performance for analysis and prediction such as provide a high accuracy at 84% to analyze breast cancer in research of Dalwinder *et al.,* (2020) and over 94% accuracy for rainfall prediction in agriculture area by Vamsidhar *et al.* (2010).

The objectives of this study were to evaluate the performance of a deep learning model for prediction and analysis the water quality of the Chao Phraya River, Thailand. The supervised data (labeling data) of water quality were collected from 2007 to 2019 and processed using a deep learning model of multi-layer feed-forward artificial neural network with back-propagation algorithm from RapidMiner program. The rest of the paper is organized as follows. Section 2 (material and method) describes the pre-process of collected data from the study area, designed system architecture, and process for implementation and valuation. Section 3 (results and discussions) represents the results and discussion, which is analyzed by an approach.

2. Material and method

2.1 Data collection and pre-processing

The study area was the Chao Phraya River in Thailand, which has a catchment of 177,000 square kilometers (99.00'E – 101.30'E, 13.15'N – 17.00'N). The Chao Phraya River is formed by the Wang and Ping Rivers that merge into the Ping River and another main river formed by the Yom and Nan Rivers into the Nan River. The Chao Phraya River flows through the central region of Thailand, though the capital Bangkok and then into the Gulf of Thailand (PCD, 2018; Veesommai and Kiyoki, 2015), as shown in Figure 1.

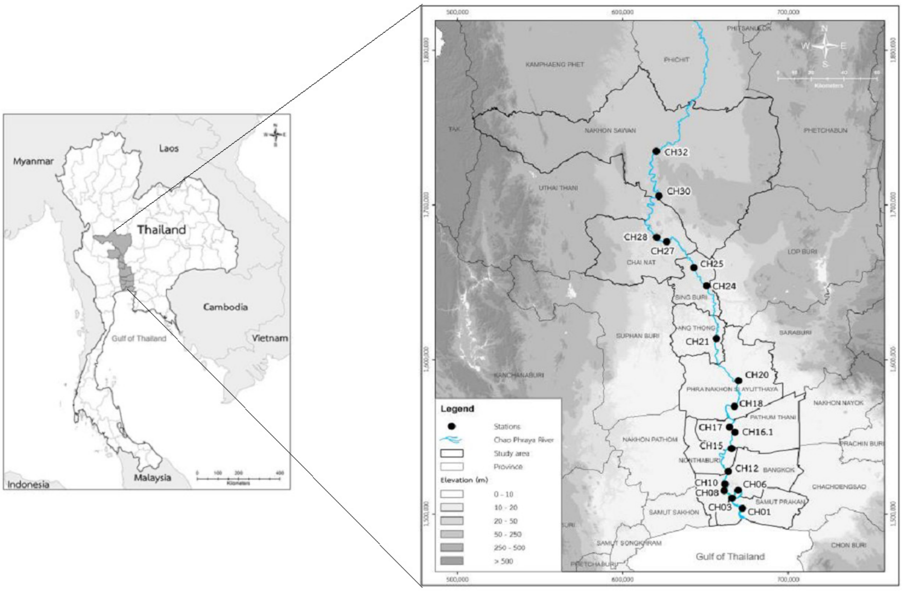

Figure 1. Map of Chao Phraya River catchment in central Thailand

The dataset in this study consist of two parts; metadata of water attributes and calculated data (WQI). The metadata used in the study were collected from the Freshwater Sector, Pollution Control Department (PCD), Ministry of Natural Resources and Environment, Thailand (PCD, 2018). The dataset consisted of 12 water attributes: turbidity (Turb, NTU), conductivity (Cond, µS), total solids (TS, mg/L), total dissolved solid (TDS. mg/L), suspended solids (SS, mg/L), dissolved oxygen (DO, mg/L), biological oxygen demand (BOD, mg/L), nitrate-nitrogen (NO_3-N, mg/L), ammonia-nitrogen (NH_3-N, mg/L), salinity (Sal, ppt), total coliform bacteria (TCB, MPN/100 ml), fecal coliform bacteria (FCB, MPN/100 ml). The collected data above will be preprocessing with (i) review and select crucial attributes to compute in an approach based on theirs's impacts on water quality and (ii) normalize unstructured data such as the unit of attributes and data type. The calculated data (WQI) is computed by weighted arithmetic water quality index method from multiple water attributes into singer value to represent the class of water quality. Then rating class according to WQI score as (i) score 0 to 25 represent excellent water quality, (ii) score 26 to 50 shown good water quality, (iii) score 51 to 75 proved the poor water quality, (iv) score 76 to 100 descript at very poor water quality, and (v) score above 100 means unsuitable water quality (Tyagi *et al.,* 2013)

2.2 System architectural design

The study team designed and implemented the system architecture for the deep learning model and its use to predict river water quality classes. The system architecture consisted of 2 parts: the dataset part and the implementation part. The dataset part was divided into 2 sections: a training dataset and a testing dataset, with both datasets including water quality data and spatial-temporal data. The implementation was divided into 2 procedures: model implementation and model prediction. The system design architecture is shown in Figure 2.

2.3 Model implementation and prediction

The system architecture consisted of 2 procedures: model implementation for teaching and model prediction of river water quality. Implementation used the RapidMiner studio program (9.5.001) and 905 datasets from 2007 to 2019, collected from the metadata of the Freshwater Department, Ministry of Environment, Thailand. This dataset was divided into 2 parts: a dataset of preform model for the training and testing model (90% of total dataset) and a dataset of evaluation for the testing model (10% of total dataset).

Procedures 1: Model implementation

First, we implemented the prediction model from the DL model. This procedure contained 4 steps for the training model using 90% of the total dataset:

Step 1: Import dataset of preform model to the system

The pre-processing data was imported into the system as a training dataset.

Step 2: Select attribute

- The selected attribute criteria were set for the prediction using by filtering function
- The input and output attributes were set for training the DL model.

Step 3: Set the role

The criteria were set for the role to implement the prediction result by labeling the output attributes in the system.

Step 4: Training and testing the model

The main part (90%) of the total dataset was used to train the model in the cross validation (CV) function of the system for efficiency analysis. Those data will be divided into two parts; first part for training and build DL model and second part for testing DL model. The CV function consisted of 2 sections: training and testing. The dataset was divided into 10 subsets for 10 - fold CV or 10 iterations. In the first iteration, the dataset on 1 - 9 were used to develop and train the model and the datasets on 10 was tested and validation. Then the second iteration, the dataset on 1 - 8 and 10 were used and the dataset on 9 was tested and validation. And other iterations continued until the last dataset had been used for training.

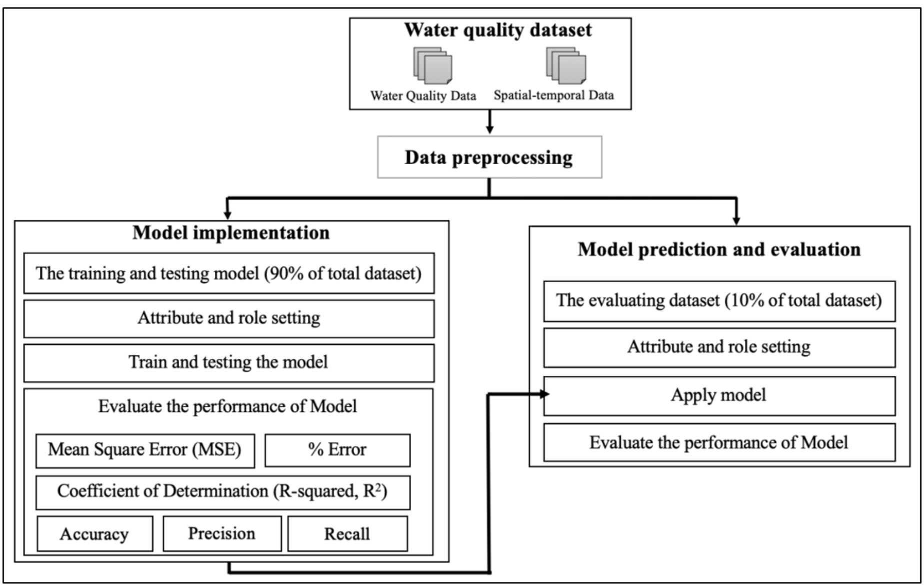

Figure 2. System design architecture used in the study

Step 5: Evaluate performance of model

The performance was evaluated based on the mean square error (MSE) as shown in equation 1, the coefficient of determination (R^2) as shown in equation 2 and the %error as shown in equation 3, accuracy as shown in equation 4, precision as shown in equation 5, and recall as shown in equation 6.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - \hat{X}_i)^2 \quad (1)$$

$$R^2 = 1 - \frac{\sum_i (X_i - \hat{X}_i)^2}{\sum_i (X_i - \mu)^2} \quad (2)$$

$$\%\, error = \left|\frac{\hat{X} - X_i}{X_i}\right| x\ 100 \quad (3)$$

Where

n = the number of datasets.

X_i = the actual value.

$\hat{X}_i$ = the predicted value.

μ = the mean of total X in the dataset.

$$Accuracy = \frac{TP+TN}{p+N} \quad (4)$$

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

Where

TP = true positives.

FP = false positives.

FN = false negatives.

TN = true negatives.

P = condition positives.

N = condition negatives.

Procedures 2: Model prediction and evaluation

In the second procedure, we analyzed the performance of the prediction model using the evaluating dataset in the DL models. The evaluating dataset consisted of 90 datasets (10% of total dataset) from 2018 to 2019. There were 5 steps in this procedure:

Step 1: to import a dataset of evaluation to the system

In this step, we import all evaluating dataset, which is from pre-processing process, into system. This dataset will be implemented the prediction result.

Step 2: to select attribute

In this step, we set the criteria of attribute, which is a same criterion of training dataset to evaluating dataset

Step 3: to set role

In this step, we set the criteria of role for implement the prediction result, which is a same criterion of training dataset to evaluating dataset

Step 4: to apply model

In this step, we applied evaluating dataset into model from the first procedure for prediction the water quality of river.

Step 5: Evaluate the predicted performance

The evaluation of predicted performance step, we evaluated the predicted performance by compare DL predicted result with actual results

3. Result and Discussion

3.1 Collected and pre-processed data

We collected 905 datasets regarding the water quality of the river with 12 attributes. For the pre-processing data process, the pattern of the datasets was suitable for model implementation based on data type and data variance. The attribute selection process identified 5 attributes (DO, BOD, NH_3-N, FCB, and TCB) based on the PCD water quality analysis criteria, where DO was in the range from 0.10 to 10.00 mg/L with a mean of 4.07 mg/L, BOD was in the range from 0.10 to 12.80 mg/L with a mean of 2.32 mg/L, NH_3-N was in the range from 0.01 to 8.22 mg/L with a mean of 0.47 mg/L, TCB was in the range from 200 to 170,000 with a mean of 25,293 (MPN/100 ml), and FCB was in the range from 200 to 160, 000 with a mean of 8,970 (MPN/100 ml).

Five attributes selected in this study represented the quality of water. DO is an indication of the clean quality of water, which represents the measuring dissolved oxygen in the water. BOD is an index of wastewater that could refer to unclean or poor water. NH_3-N is guiding factor to show the poor quality of water from municipal water usage. TCB and FCB are biological water indicators that represent the number of bacteria from human and animal intestine. Therefore, those attributes are important to use for water quality analysis and classification

3.2 System architectural design of model

From the system architecture of the model, we implemented the DL model by using the RapidMiner studio program (9.5.001) on a MacBook Pro (2017, 3.5 GHz Dual-Core Intel Core i7) laptop, which is shown in Figure 3. The input dataset (training dataset and testing dataset) is represented by the purple box. The attribute selection and role setting discussed in 2.3 above are shown by the pink box. The yellow box (`CV_Deep Learning`) implements of the preform model. Within the `CV_Deep Learning` box, the DL model is trained and tested as shown in Figure 4. The evaluating dataset was applied to the green box (`Apply Model(2)`) to analyze the prediction results. Lastly, the second yellow box of `Performance(2)` analyzed the precision, recall and accuracy of the prediction result.

3.3 Implemented and predicted Model

Result from procedure 1: implemented Model

The model had a good fit to the data with the R^2 and MSE values from the first cycle training being 0.81 and 0.40, respectively, with a training speed performs at 14,553 rows/sec (0.088 sec total training) on a MacBook Pro (2017, 3.5 GHz Dual-Core Intel Core i7) laptop. After the final iteration of training (in the 10-fold cross validation), the model had R^2 and MSE values of 0.90 and 0.20, respectively, with a training speed performs at 18,607 rows/sec (0.479 sec total training) on the same laptop. The prediction result from model implementation compared with the actual water quality classes are shown in Table 1. The matched and missing prediction result with the actual data is found in 5 level of water quality class as 1) unsuitable water

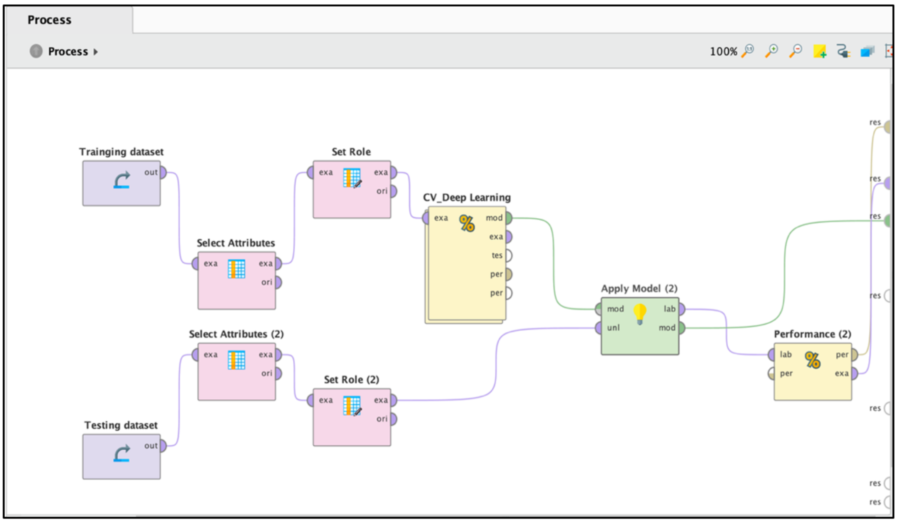

Figure 3. The implemented the DL model by using the RapidMiner studio program

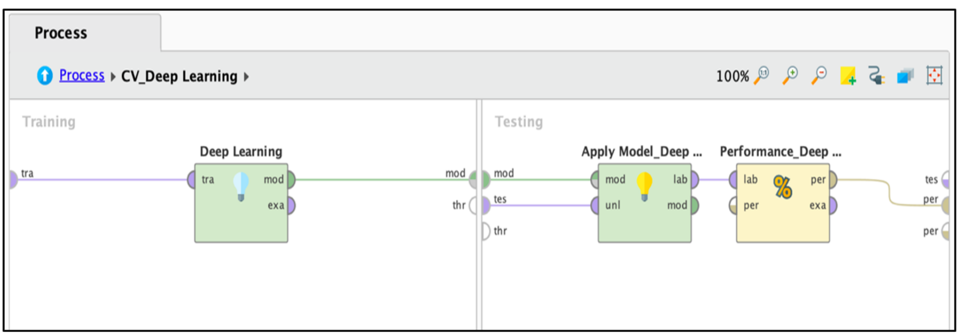

Figure 4. The performing process of DL model in `CV_Deep Learning` box by using the RapidMiner studio program

quality class was 284 times from 285 times (missing 1 time), 2 very poor water quality class was 129 times from 184 times (missing 55 times), 3) poor water quality class was 216 times from 239 times (missing 23 times), 4 good water quality class was 69 times from 72 times (missing 3 times), and 5) excellent water quality class was 27 times from 35 times (missing 8 times).

The training DL model had high accuracy for water quality prediction at 88.96% with 11.04% error results compared to the actual results. For the precision of DL model for prediction results, the model contributed 99.65%, 95.83%, 90.38%, 70.11%, and 77.14% for the unsuitable water quality class, very poor water quality class, poor water quality class, good water quality class, and excellent water quality class, respectively. The recall results also indicated that the DL model performed well with 92.51%, 95.56%, 93.10%, 72.63%, and 86.75% in the unsuitable, very poor, poor, good, and excellent quality class, respectively. The evaluated the performance of model using 4 methods: %error, accuracy, precision, and recall, as shown in Table 2.

Result from procedure 2: Model prediction and evaluation

After an evaluating dataset had been applied to model, the prediction results were similar to the actual results, as shown in Figure 5 for the results in 162 results in 5 classes of water quality (unsuitable water, very poor water, poor water, good water, and excellent water quality class). The dotted line represents the prediction result and the bold line represents the actual result.

The results from the evaluating procedure found that the DL approach provided 80 corrected prediction results (88.89%) when compared with the actual data (total 90 actual data). The 10 incorrect prediction result (11.11%) was 1 incorrect prediction result from very poor water class to poor water class, 6 incorrect prediction result from good water class to poor water class, and 3 incorrect prediction result from excellent water class to good water class. While gave all corrected predictions result in unsuitable water and poor water class.

Table 1. Results of training in implementing the deep learning model

Actual result / Predicted result	true excellent water	true good water	true poor water	true very poor water	true unsuitable
pred. excellent water	27	8	0	0	0
pred. good water	2	69	1	0	0
pred. poor water	0	18	216	5	0
pred. very poor water	0	0	23	129	23
pred. unsuitable water	0	0	0	1	284

Remark: Orange color is represented the amount of the predicted result that meet with the actual result

Table 2. Performance of training in building deep learning model

Class / Performance	Unsuitable water	Very poor water	Poor water	Good water	Excellent water
Accuracy			88.96%		
Total error			11.04%		
Class precision	99.65%	95.83%	90.38%	70.11%	77.14%
Class recall	92.51%	95.56%	93.10%	72.63%	86.75%
Confidence class	0.36	0.22	0.26	0.10	0.06

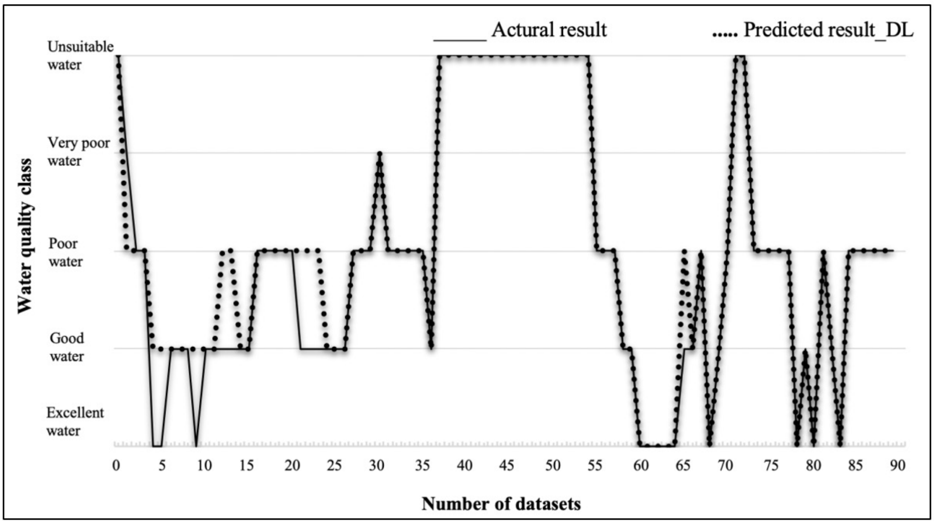

Figure 5. Prediction results of water quality using deep learning model

The results above indicated that the DL model based Multi-layer Feed-forward Artificial Neural Network with Backpropagation Algorithm can apply and predict water class of river water quality field. Implemented DL model represents a potential result for water quality prediction, which is over 90.38% precision in three water quality classes (unsuitable, very poor and poor). While two water quality classes (good and excellent) was 70.11-77.14% due to small amount of dataset that meet with those. To increase ratio of dataset with good and excellent classes, it could be possible to obtain more accurate results. The related condition and results were reported in prediction of heavy rain damage by Lee *et al.* (2020) and prediction of solar radiation by Premalatha and Valan Arasu (2016). The apply the implemented DL model (model prediction and evaluation) to other dataset demonstrated the similar accuracy for prediction the river water quality classes in order to confirm the suitability of the model. According to the results shown high accuracy (88.89%) and some of missing classes result from apply model was similar trend with implemented model. As well as, water quality data is a dynamic changing if the water quality measured for the continuous in various periods and time series data are included as input data for prediction, the DL model approach also would be contributed more precise results. One of the alternatives of this DL model approach, the complicated calculation method and calculated time problem by manual method were minimized with 0.479 sec/dataset. Similar to the successes in other fields (Svetnik *et al.,* 2003; Ayon and Islam, 2019; Deag *et al.,* 2013). Thus, all of the results of this study were addressed the ability of DL model based Multi-layer Feed-forward Artificial Neural Network with Backpropagation Algorithm for prediction the water quality classes with two procedures (implemented model and model prediction and evaluation). In the future work, this DL model approach can be improve and utilize to this study area or other environmental area by (i) the different water resource (ground water, sea water and coastal water) would be apply for increasing the feasible model, (ii) the other significant of water parameter can be include for represent the over all of water quality, and (iii) the system design architecture of this study able to expand to other environmental prediction such as plastic debris.

4. Conclusion

The DL model based Multi-layer Feed-forward Artificial Neural Network with Backpropagation Algorithm predicts the water quality from database information collected by the Pollution Control Department (PCD), Thailand and RapidMiner studio program. DO, BOD, NH_3-N, TCB, and FCB from 2007–2019 were analyzed. The predicted results of DL model in this study had satisfactory performance in predicting the quality of the river water. Using 90% of the dataset to train the DL model using 10-fold cross validation produced values for R^2 of 0.90 and MSE of 0.20 involving 0.479 sec of training time. The training DL approach provided 88.96% accuracy for water quality prediction. Then, the 10% of the dataset used to evaluate the DL model had a predicted accuracy of 88.89%. The DL model was more precise in predicting unsuitable and poor water quality classes by contributed all correctly predicted results. To improve the prediction precision for the good and excellence water quality classes, increased amounts of data from these classes should be added into the training procedure. The deep learning model was able to analyze the large dataset of water quality in this study at a rate of 18,607 rows of data/sec (within 0.479 sec). Therefore, the DL model for water quality prediction is a promising alternative to current measures and can be recommended for water quality data implementation and analysis in this field and in other environmental data studies in the future.

Declaration of competing interest

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

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