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Water Quality Index Process Using Artificial Neural Networks

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ABSTRACT

This Study intends to explore the association among the water quality record (WQI) for water framework drives four free environment factors. Our logical examination was driven on the Euphrates River inside Karbala city, Iraq over the period between 2008 to 2021.The nonlinear backslide perfect was gotten to base the WQI since the coefficient of affirmation and least mix-up regard stayed improved than persons gained by the ANN. The outcomes got in this exhibit that the LM strategy is more proficient and viable in catching the non-direct and complex spillover measure in a huge Indian catchment.

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1. INTRODUCTION

Water quality is the most significant factor influencing fish wellbeing and execution in hydroponics creation frameworks. Great water quality alludes to what the fish needs and not what we think the fish needs. This implies we should comprehend the water quality prerequisites of the fish under culture well overall. Fish live and are absolutely reliant on the water they live in for every one of their needs [1,2,3,4,5]. Diverse fish species have extraordinary and explicit scope of water quality viewpoints inside which they can endure, develop and repeat [6,7,8,9,10].

Inside these resilience restricts, every species has its own ideal range, that is, the range inside which it performs best [11,12]. It is in this way significant for fish makers to guarantee that the physical and compound states of the water stay, however much as could be expected, inside the ideal scope of the fish under culture constantly [13,14,15].

Outside these ideal extents, fish will display helpless development, flighty conduct, and malady side effects or parasite pervasions. Under outrageous cases, or where the helpless conditions stay for delayed timeframes, fish mortality may happen. Lake water contains two significant gatherings of substances:

- Suspended particles made of non-living particles and little plants and creatures, the microscopic fish.
- Dissolved substances made of gases, minerals and natural mixes.

The structure of lake water changes ceaselessly, contingent upon climatic and occasional changes, and on how a lake is utilized. It is the point of good administration to control the organization to yield the best conditions for the fish. For makers to have the option to keep up ideal lake water quality conditions, they should comprehend the physical and compound segments adding to fortunate or unfortunate water quality [16,17,18].

The Kinta River is the largest of three rivers that pass through Ipoh. It flows from Gunung Korbu in Ulu Kinta, which is roughly 2000 metres above sea level, to the Perak River, which is about 100 kilometres to the south west of the headwater. The Kinta River and its tributaries drain a basin that is about 2420 km^2 in size. The catchment's geography includes steep, forested limestone hills and mountains to the north and east of Ipoh, as well as a valley (Kinta Valley) to the south. Following the headwaters, the Kinta River flows through heterogeneous, mixed-use terrain, with mining, rubber growing, oil palm cultivation, urban development, and logging among the major land uses in the basin.

The Kinta River is Ipoh's most important water supply, and Perak's second most important water source. It is Ipoh's primary supply of drinking and irrigation water, as well as a major tributary of the Perak River, Perak's primary source of drinking and irrigation water. On the Kinta River, there is now only one dam. It was built in the year 2000 with the goal of increasing Perak's water supply by 25%. This dam can provide 639,000 m^3 of water per day and is intended to provide Kinta Valley's water needs until 2020[19,20,21].

2. MODEL DEVELOPMENT

Two distinct sorts of ANN spillover gauge models have been built up that vary in the way of the preparation strategy utilized. The principal sort of Artificial Neural Network (ANN) model utilizes the well-known first request angle plummet BPA and the second kind of ANN model utilizes the second request LM strategy. The everyday overflow information got from the Godavari River catchment are utilized to build up all the ANN models. A concise outline of the examination region and information utilized is first given before giving the subtleties of the ANN model turn of events [22,23,24].

As a result, calculating such WQIs requires time and effort, and it's not uncommon for unintended errors to occur during sub-index calculations. This argument is not intended to diminish or undervalue these well-established indices, which have proven to be highly successful and useful in practise due to their scientific foundation. Rather, we provide an alternative, direct, and fast method of computing and forecasting WQI values based on artificial neural network (ANN) modelling, which has the potential to cut computation time and effort while also reducing the chance of calculation errors. As a result, this research shows how to create a neural network model for quick, direct WQI calculation as an alternative to WQI computation approaches that need sub-indexing and extensive calculations.

2.1 The water quality parameters

Since February 1997, the Department of Environment (Malaysia) has been conducting regular monitoring of the quality of Kinta River water for seven months each year (February, March, May, June, August, September, and November). There were 9180 data points in this dataset, which came from 36 measurements on 255 samples. It provides values for a set of water pollution indicators for monitoring locations in the upper, middle, and lower sections of the river basin, beginning 15.4 kilometres downstream of the river's headwater at Gunung Korbu and ending 17.2 kilometres upstream of the Kinta River's confluence with the Perak River.

2.2 Study Area and Data

The overflow information got from Godavari River, India were utilized to test the proposed technique in this investigation. The everyday normal overflow esteems at Polavaram station were utilized. The Polavaram station is situated inside the Godavari River Basin in Andhra Pradesh, India (see Figure 2). The catchment has a region of 307,800 km2 roughly. 34 years of every day spillover information from 02-11-1966 to 31-05-2000, were accessible. The whole informational collection was isolated into preparing, approval and testing set dependent on measurable similitude according to MATLAB technique. The information were normalized utilizing direct standardization strategy in the range (0.0, 1.0).

Stream gauge station at Polavaram

Fig.1 Godavari River Basin, Andhra Pradesh, India

2.3 Artificial Neural Network Model Development

The advancement of precipitation spillover replicas utilizing ANNs, includes the accompanying advances: (I) ID of the info vector, (ii) standardization (scaling) of the information, (iii) choice of the organization engineering, (iv) deciding the ideal amount of neurons in the shrouded layer, (v) preparing of the ANN models, and (vi) approval of ANN model utilizing the chose exhibition assessment insights. Both the ANN models (ANN-GD and ANN-LM) were created utilizing the above system and is depicted beneath. The quantity of neurons in the shrouded layer was resolved utilizing an experimentation methodology by thinking about 5, 10, 15, and 20 concealed neurons. The sigmoid enactment work was utilized at concealed layer and direct initiation work was utilized at the yield layer as the exchange work.

As referenced beforehand, the ANN-GD model utilized the mainstream first request slope drop BPA utilizing group learning with force factor for its preparation. The benefit of learning coefficient of 0.01 and force rectification factor of 0.075 was utilized while preparing. The estimation of N was changed as 5, 10, 15, and 20 and for each estimation of N, the main request inclination drop BPA was utilized to limit mean squared blunder (MSE) at the yield layer. The advancement of the ANN-LM model was completed utilizing a similar system aside from that LM strategy was utilized preparing. When the preparation of the best ANN models was finished, the prepared ANN models were utilized to compute different execution assessment files.

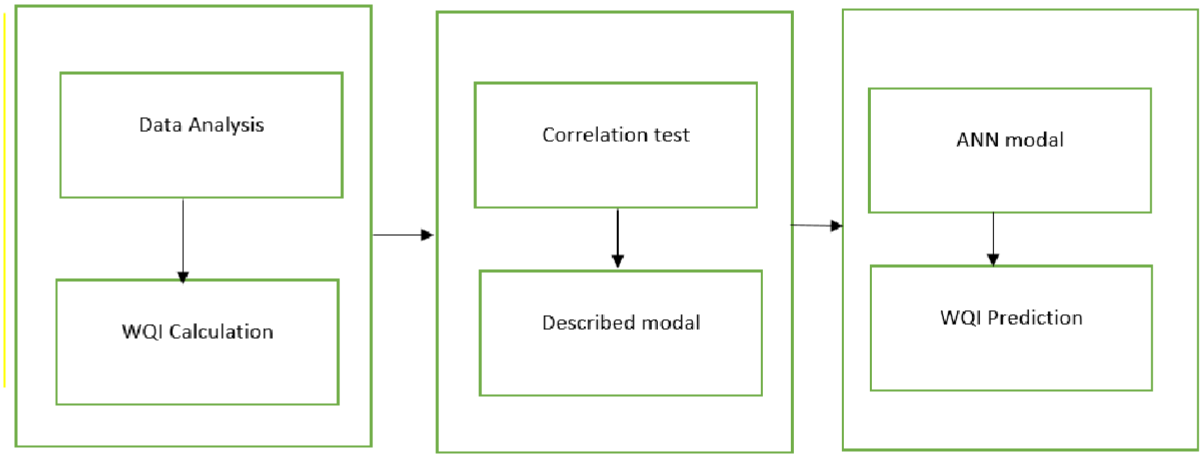

Fig.2 Flowchart of architecture of ANN models for WQI prediction

2.4 Model Performance

The demonstrations the both models created in the modal be situated assessed utilizing standard factual execution assessment measure. This was relationship coefficient (R). This factual boundary can be determined utilizing the accompanying articulation:

$$\lambda = \frac{\sum_{r=1}^{M}\left(LO(\mathrm{r})-\overline{LO}\right)\left(\mathrm{L}(\mathrm{r})-\overline{L}\right)}{\sqrt{\sum_{r=1}^{M}\left(LO(\mathrm{r})-\overline{LO}\right)^{2}\left(\mathrm{L}(\mathrm{r})-\overline{L}\right)^{2}}}$$

The L*O*(r) is the practical runoff at time r, L(r) is the valued runoff at time r, M is the whole given number of excess data ideas valued since an ANN model, and *LO* is the mean experiential extra, L is the mean probable runoff.

3. RESULTS DISCUSSION

The connection coefficient is an ordinarily utilized measurement and gives data on the quality of straight connection between the watched and the figured qualities.

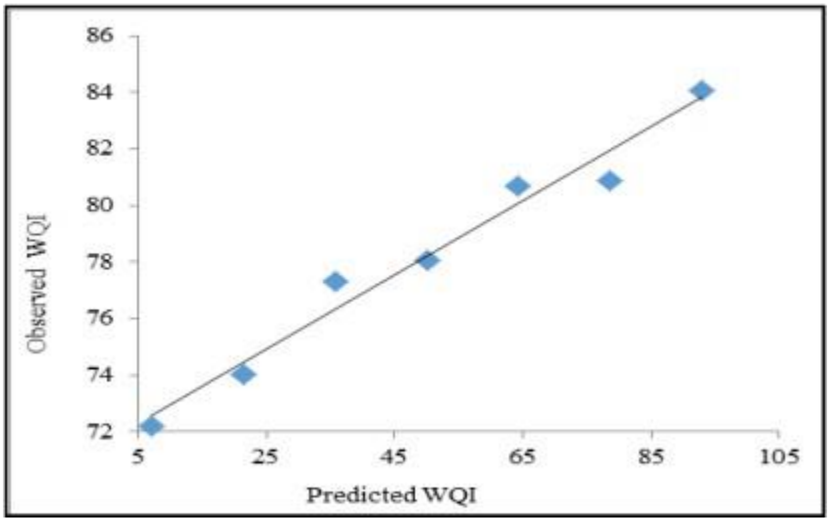

Fig.3 Results for ANN 5-20-1 LM

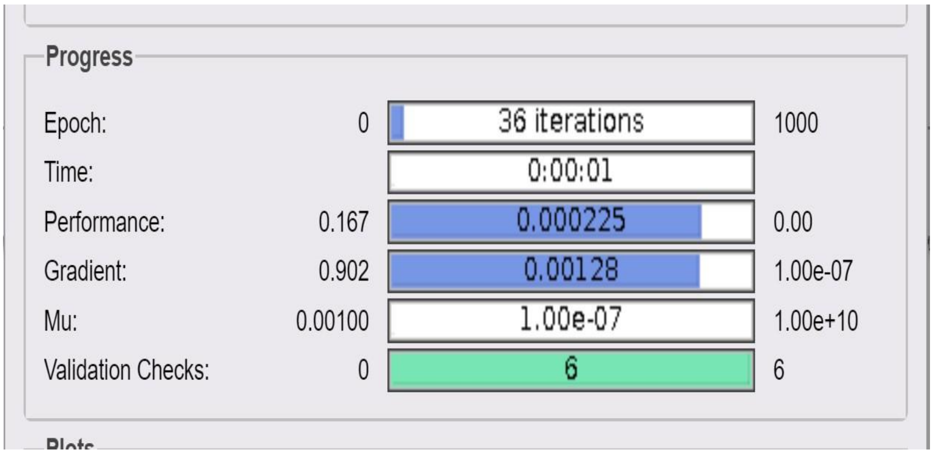

Fig.4 Results for ANN 5-15-1 LM

ANN MODEL	Values of R		
	During Training	During Testing	During Validation
ANN 5-20-1 LM	0897441	0.986	0896658
ANN 5-15-1 LM	0897285	0896556	0.87395
ANN 5-10-1 LM	0.87397	0.86571	0.97216
ANN 5-5-1 LM	0.87141	0.86763	0.87371
ANN 5-20-1 GD	0.86577	0.88485	0.77556
ANN 5-15-1 GD	0.89441	0.8335	0.73491
ANN 5-10-1 GD	0.78303	0.79072	0.74782
ANN 5-5-1 GD	0.79685	0.769094	0.73055

Table.1 Statistical Performance Evaluation Measures from Various ANN Models

The quantifiable modal connection investigation was utilized to decide the huge data sources, which were discovered to be spillovers in the past up to 5 time steps. The best ANN engineering was dictated by changing the quantity of shrouded neurons as 5, 10, 15, and 20. The best ANN engineering for ANN-GD and the ANN-LM models were resolved to be 5-20-1 and 5-10-1, individually. A wide assortment of standard factual execution assessment measures were utilized to assess the exhibitions of different ANN models created. Disperse plots were utilized as graphical assessment

4. CONCLUSIONS

This article we present the discoveries of an investigation of examination of two distinctive preparing strategies for preparing ANN models for spillover determining in Godavari River, India. The preparation strategies researched incorporate the well-known back-spread calculation (BPA) and the Levenberg-Marquardt preparing calculation. The everyday normal overflow information got from the Godavari River bowl, USA were utilized to build up the two ANN models examined in this investigation. Connection investigation was utilized to decide the huge data sources, which were discovered to be spillovers in the past up to 5 time steps.

The best ANN engineering was dictated by changing the quantity of shrouded neurons as 5, 10, 15, and 20. The best ANN engineering for ANN-GD and the ANN-LM models were resolved to be 5-20-1 and 5-10-1, individually. A wide assortment of standard factual execution assessment measures were utilized to assess the exhibitions of different ANN models created. Disperse plots were utilized as graphical assessment.

For the training, testing, and validating sets, the ANN model has a correlation coefficient of 0.8882 and MSE values of 0.0252, 0.2231, and 1.4344, respectively. These findings were acquired using the Neural Network Fitting software and the Levenberg– Marquardt algorithm for training, with the following set division: training (70%), validation (15%), and testing (15%).

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