Literature servey:

Efficient Water Quality Prediction Using Supervised Machine Learning

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Abstract: Water makes up about 70% of the earth's surface and is one of the most important sources vital to sustaining life. Rapid urbanization and industrialization have led to a deterioration of water quality at an alarming rate, resulting in harrowing diseases. Water quality has been conventionally estimated through expensive and time-consuming lab and statistical analyses, which render the contemporary notion of real-time monitoring moot. The alarming consequences of poor water quality necessitate an alternative method, which is quicker and inexpensive. With this motivation, this research explores a series of supervised machine learning algorithms to estimate the water quality index (WQI), which is a singular index to describe the general quality of water, and the water quality class (WQC), which is a distinctive class defined on the basis of the WQI. The proposed methodology employs four input parameters, namely, temperature, turbidity, pH and total dissolved solids. Of all the employed algorithms, gradient boosting, with a learning rate of 0.1 and polynomial regression, with a degree of 2, predict the WQI most efficiently, having a mean absolute error (MAE) of 1.9642 and 2.7273, respectively. Whereas multi-layer perceptron (MLP), with a configuration of (3, 7), classifies the WQC most efficiently, with an accuracy of 0.8507.

The proposed methodology achieves reasonable accuracy using a minimal number of parameters to validate the possibility of its use in real time water quality detection systems. Keywords: water quality prediction; supervised machine learning; smart city; gradient boosting; multi-layer perceptron 1. Introduction Water is the most important of sources, vital for sustaining all kinds of life; however, it is in constant threat of pollution by life itself. Water is one of the most communicable mediums with a far reach. Rapid industrialization has consequently led to deterioration of water quality at an alarming rate. Poor water quality results have been known to be one of the major factors of escalation of harrowing diseases. As reported, in developing countries, 80% of the diseases are water borne diseases, which have led to 5 million deaths and 2.5 billion illnesses [1]. The most common of these diseases in Pakistan are diarrhea, typhoid, gastroenteritis, cryptosporidium infections, some forms of hepatitis and giardiasis intestinal worms [2]. In Pakistan, water borne diseases, cause a GDP loss of 0.6–1.44% every year [3]. This makes it a pressing problem, particularly in a developing country like Pakistan. Water quality is currently estimated through expensive and time-consuming lab and statistical analyses, which require sample collection, transport to labs, and a considerable amount of time and Water 2019, 11, 2210; doi:10.3390/w11112210 www.mdpi.com/journal/water Water 2019, 11, 2210 2 of 14 calculation, which is quite ineffective given water is quite a communicable medium and time is of the essence if

water is polluted with disease-inducing waste [4]. The horrific consequences of water pollution necessitate a quicker and cheaper alternative.

In this regard, the main motivation in this study is to propose and evaluate an alternative method based on supervised machine learning for the efficient prediction of water quality in real-time. This research is conducted on the dataset of Rawal water shed, situated in Pakistan, acquired by The Pakistan Council of Research in Water Resources (PCRWR) (Available online at URL http://www.pcrwr.gov.pk/). A representative set of supervised machine learning algorithms were employed on the said dataset for predicting the water quality index (WQI) and water quality class (WQC). The main contributions of this study are summarized as follows: •

A first analysis was conducted on the available data to clean, normalize and perform feature selection on the water quality measures, and therefore, to obtain the minimum relevant subset that allows high precision with low cost. In this way, expensive and cumbersome lab analysis with specific sensors can be avoided in further similar analyses. • A series of representative supervised prediction (classification and regression) algorithms were tested on the dataset worked here. The complete methodology is proposed in the context of water quality numerical analysis. • After much experimentation, the results reflect that gradient boosting and polynomial regression predict the WQI best with a mean absolute error (MAE) of 1.9642 and 2.7273, respectively, whereas multi-layer perceptron (MLP) classifies the WQC best, with an accuracy of 0.8507. The remainder of this paper is organized as follows: Section 2 provides a literature review in this domain. In Section 3, we explore the dataset and perform preprocessing. In Section 4, we employ various machine learning methodologies to predict water quality using minimal parameters and discuss the results of regression and classification algorithms, in terms of error rates and classification precision. In Section 5, we discuss the implications and novelty of our study and finally in Section 6, we conclude the paper and provide future lines of work. 2. Literature Review This research explores the methodologies that have been employed to help solve problems related to water quality. Typically, conventional lab analysis and statistical analysis are used in research to aid in determining water quality, while some analyses employ machine learning methodologies to assist in finding an optimized solution for the water quality problem. Local research employing lab analysis helped us gain a greater insight into the water quality problem in Pakistan.

In one such research study, Daud et al. [5] gathered water samples from different areas of Pakistan and tested them against different parameters using a manual lab analysis and found a high presence of E. coli and fecal coliform due to industrial and sewerage waste. Alamgir et al. [6] tested 46 different samples from Orangi town, Karachi, using manual lab analysis and found them to be high in sulphates and total fecal coliform count. After getting familiar with the water quality research concerning Pakistan, we explored research employing machine learning methodologies in the realm of water quality. When it comes to estimating water quality using machine learning, Shafi et al. [7] estimated water quality using classical machine learning algorithms namely, Support Vector Machines (SVM), Neural Networks (NN), Deep Neural Networks (Deep NN) and k Nearest Neighbors (kNN), with the highest accuracy of 93% with Deep NN. The estimated water quality in their work is based on only three parameters: turbidity, temperature and pH, which are tested according to World Health Organization (WHO) standards (Available online at URL https://www.who.int/airpollution/guidelines/en/). Using only three parameters and comparing them to standardized values is quite a limitation when predicting water quality. Ahmad et al. [8] employed single feed forward neural networks and a combination of multiple neural networks to Water 2019, 11, 2210 3 of 14 estimate the WQI. They used 25 water quality parameters as the input. Using a combination of backward elimination and forward selection selective combination methods,

they achieved an R2 and MSE of 0.9270, 0.9390 and 0.1200, 0.1158, respectively. The use of 25 parameters makes their solution a little immoderate in terms of an inexpensive real time system, given the price of the parameter sensors. Sakizadeh [9] predicted the WQI using 16 water quality parameters and ANN with Bayesian regularization. His study yielded correlation coefficients between the observed and predicted values of 0.94 and 0.77, respectively. Abyaneh [10] predicted the chemical oxygen demand (COD) and the biochemical oxygen demand (BOD) using two conventional machine learning methodologies namely, ANN and multivariate linear regression. They used four parameters, namely pH, temperature, total suspended solids (TSS) and total suspended (TS) to predict the COD and BOD.

Ali and Qamar [11] used the unsupervised technique of the average linkage (within groups) method of hierarchical clustering to classify samples into water quality classes. However, they ignored the major parameters associated with WQI during the learning process and they did not use any standardized water quality index to evaluate their predictions. Gazzaz et al. [4] used ANN to predict the WQI with a model explaining almost 99.5% of variation in the data. They used 23 parameters to predict the WQI, which turns out to be quite expensive if one is to use it for an IoT system, given the prices of the sensors. Rankovic et al. [12] predicted the dissolved oxygen (DO) using a feedforward neural network (FNN). They used 10 parameters to predict the DO, which again defeats the purpose if it has to be used for a real-time WQI estimation with an IoT system. Most of the research either employed manual lab analysis, not estimating the water quality index standard, or used too many parameters to be efficient enough. The proposed methodology improves on these notions and the methodology being followed is depicted in Figure 1. Water 2019, 11, x FOR PEER REVIEW 3 of 14 three parameters and comparing them to standardized values is quite a limitation when predicting water quality. Ahmad et al. [8] employed single feed forward neural networks and a combination of multiple neural networks to estimate the WQI. They used 25 water quality parameters as the input. Using a combination of backward elimination and forward selection selective combination methods, they achieved an R2 and MSE of 0.9270, 0.9390 and 0.1200, 0.1158, respectively. The use of 25 parameters makes their solution a little immoderate in terms of an inexpensive real time system, given the price of the parameter sensors. Sakizadeh [9] predicted the WQI using 16 water quality parameters and ANN with Bayesian regularization. His study yielded correlation coefficients between the observed and predicted values of 0.94 and 0.77, respectively. Abyaneh [10] predicted the chemical oxygen demand (COD) and the biochemical oxygen demand (BOD) using two conventional machine learning methodologies namely, ANN and multivariate linear regression. They used four parameters, namely pH, temperature, total suspended solids (TSS) and total suspended (TS) to predict the COD and BOD. Ali and Qamar [11] used the unsupervised technique of the average linkage (within groups) method of hierarchical clustering to classify samples into water quality classes. However, they ignored the major parameters associated with WQI during the learning process and they did not use any standardized water quality index to evaluate their predictions. Gazzaz et al. [4] used ANN to predict the WQI with a model explaining almost 99.5% of variation in the data. They used 23 parameters to predict the WQI, which turns out to be quite expensive if one is to use it for an IoT system, given the prices of the sensors. Rankovic et al. [12] predicted the dissolved oxygen (DO) using a feedforward neural network (FNN). They used 10 parameters to predict the DO, which again defeats the purpose if it has to be used for a real-time WQI estimation with an IoT system. Most of the research either employed manual lab analysis, not estimating the water quality index standard, or used too many parameters to be efficient enough.

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