

## Web-Based Decision Support System for Water Quality Monitoring and Prediction for Outdoor Microalgae Cultivation

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**Abstract:** *In outdoor microalgae cultivation, water quality monitoring is essential for identifying any existing problem or any issues that could emerge in the future. It is very helpful in maintaining the water parameters to its optimum level to prevent unexpected death of microalgae. In outdoor cultivation, the temperature of the environment is changing which makes the blooming of microalgae less predictable. Since the environment is not controlled, the monitoring of water quality status becomes more demanding. There is a need for a web-based Decision Support System (DSS) that allows monitoring of water quality anytime, anywhere; and predicts future water quality. This study involves the development of a web-based software that allows entry of current values and predicts future values of the primary water quality parameters for outdoor microalgae cultivation: salinity and temperature. The value and status of the predicted salinity and temperature is based on historical data and current state using the similarity-based classification technique K-Nearest Neighbor (KNN). The DSS informs the user about the rise and fall of salinity and temperature either beyond or below standard level and gives suggestion of what action needs to be done to maintain the water quality parameters to optimum level. Cross validation is performed to determine the best fit parameter of 19, using the criteria of Mean Squared Error of regression in KNN. Using Mean Absolute Percentage Error (MAPE), the forecast accuracy rate of temperature and salinity are computed as 96.98% and 98.92% respectively. There is no significant difference between the suggested water to be added by the DSS and by the aquatic experts thus, the DSS can be utilized for water quality prediction.*

**Keywords:** *Decision Support System, Water Quality Monitoring, Forecasting System, Microalgae Cultivation, K-Nearest Neighbors*

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### I. Introduction

Microalgae are unicellular and can be found in solitary cells or in groups of single cells connected together and are similar to terrestrial plants in which they contain chlorophyll and require sunlight in order to live and grow. They can bloom very rapidly, much faster than any other plants and can be cultivated anywhere that receives sunlight [1]. It uses its energy to convert carbon dioxide (CO<sub>2</sub>) into sugars and oxygen; in this way they largely contribute to the oxygen animals and humans breathe. They cannot be seen with an unaided eye but when present in high numbers, they become noticeable as colored patches due to the presence of chlorophyll in their cells.

Globally, there is growing interest in microalgae as production organisms; it contains lipids (oil), proteins, and carbohydrates (sugars). Marine algae have been used as food, feed, fertilizer, and biofuel for centuries [2]. For fisher folks, it is very important to cultivate microalgae since they are used in feeding hatchlings of aquatic species which are not yet ready for regular feeds in granular form.

The cultivation of microalgae can make an important contribution to the transition to a more sustainable society, not only suitable for environmentally friendly production of many commodities, but also for the use of waste streams [3]. The EnAlgae: Decision Support Toolset is a part of the Decision Support System (DSS) which was developed as part of Energetic Algae Project co-founded by the European Union led by Swansea University with 18 partners across the North West Europe which aims to reduce CO<sub>2</sub> emissions and dependency on sustainable energy sources in North West Europe. This DSS has a unique set of intuitive tools to inform and guide investors, technology developers, businesses, policy makers and researchers on micro and macro algae cultivation [4].

Web-based DSS have been widely used in successful water quality monitoring projects [5]. A river monitoring system improved the health of the Eden River in United Kingdom (UK). Ten (10) monitoring stations are installed to gather data on river water quality that is available to the farmers, local community and anyone who is interested. The real-time data is made available in the web utilized by the council and the public to help them improve the water quality of the river [6]. The study of Paredes et. al, focuses on the improvement of Manzanares River which is the main water supplier of a highly populated region; this river receives the wastewater from the same location which made the river highly polluted thus making it uninhabitable for aquatic organisms. The Aquatool Decision Support System Shell was used to simulate the water quality of the

Manzanares River in terms of conductivity, phosphorous, carbonaceous organic matter, dissolved oxygen, organic nitrogen ammonia and nitrates [7].

Automated water quality monitoring systems in outdoor microalgae cultivation is very important to maintain the water parameters to its optimum level to prevent unexpected death of microalgae. Since the temperature of the environment is changing, the blooming of microalgae becomes less predictable and monitoring of water quality becomes more demanding. There is a need for a web-based Decision Support System (DSS) that allows monitoring of water quality anytime, anywhere; and predicts future water quality in terms of temperature and salinity. According to the work of Wang et. al, due to bad water quality, the survival rate of aquatic species declined, so a DSS for aquaculture water quality evaluation and early warning is needed. The DSS provides the result of evaluation, early warning, and management countermeasure for the water quality and can predict factors according to the long-time monitored time of the aquaculture pond in North China [9]. According to, Xue et. al, it is necessary to conduct prediction and early warning on quality in accordance with the nutritional state and current state. Their paper aims to conduct prediction and early warning in terms of dissolved oxygen content in carp aquaculture using neural networks and decision tree by value prediction and rule based reasoning [9]. According to the Department of Environment in Australia, predictive modelling and a decision support system (DSS) will help ensure protection and maintenance of their waters. DSS provides the results of analyses of the developed models and scenarios to provide a prediction of ecological and water quality outcomes which will be indicating the reductions necessary to achieve sustainable loads [10].

Today, more than forty (40) different species of microalgae, isolated in different parts of the world are cultured as pure strains in intensive systems. In the Philippines, Bureau of Fisheries and Aquatic Resources (BFAR) is a government agency responsible for the development, improvement, management and conservation of the Philippines' fisheries and aquatic resources. And since microalgae are the primary producers of nutrients, providing an essential ecological function to all aquatic life, BFAR is cultivating them to feed other aquatic species (i.e. siganids, abalone, sandfish) that they are cultivating as well. BFAR cultivates microalgae in two phases: Indoor Cultivation and Outdoor Cultivation. Indoor cultivation is done inside the laboratory under controlled condition. It has three (3) stages namely, isolating stage, primary culture stage, and secondary culture stage. When the cultivation of microalgae inside the laboratory is successful, it will be transferred outdoor in natural tanks for mass production. This phase is very crucial since the environment is not controlled, the monitoring of water quality parameters becomes more demanding. Furthermore, due to climate change, temperature and salinity becomes unpredictable. There are cases when temperature rises unexpectedly before the scheduled monitoring, which results to sudden drop of dissolved oxygen. This leads to unexpected death of outdoor microalgae. This warrants a tool that efficiently monitors water quality parameters and automatically notifies the user about the rise and fall of the level of salinity and temperature either beyond or below standard level. Thus, a web-based decision support system that monitors water quality in real-time and accurately predicts future water quality status would be useful.

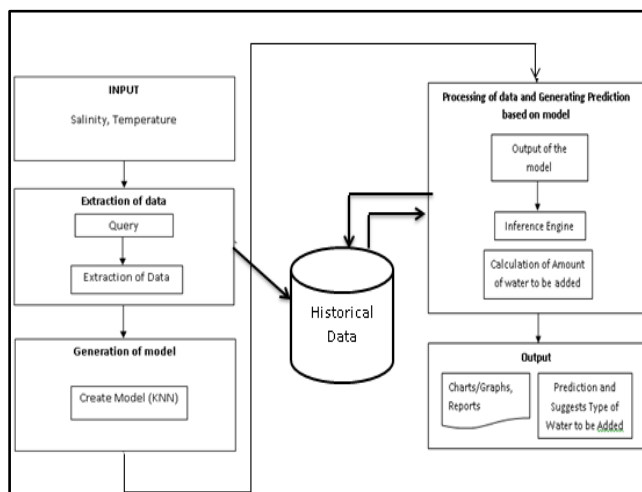
This study involves the development of a DSS, which is focused on outdoor microalgae cultivation, specifically, in increasing the rate of production by avoiding unwarranted deaths. The DSS provides a model of the current and historical water quality status through graphs and charts, and is delivered through the web. It involves predictive modeling of future water quality status in terms of temperature, salinity, pH level, D.O., and evaporation rate of the outdoor microalgae tanks water, to ensure successful outdoor microalgae cultivation.

A study conducted by Palani et.al which focuses on predicting and forecasting the quantitative characteristics of Singapore coastal waters in terms of temperature, salinity, dissolved oxygen and chlorophyll-a utilized a powerful prediction algorithm, Artificial Neural Network(ANN). Their method has the ability to represent both linear and non-linear relationships and learn these relationships directly from the data being modelled [10]. This study will attempt to utilize and determine the forecast accuracy rate of a faster but less powerful technique in terms of prediction, the K-Nearest Neighbors (KNN).

## **II. Methods**

### **3.1 Software Development**

Using KNN as data mining technique, the web-based DSS was developed to forecast future water temperature and salinity levels in the form of graphs and charts, utilizing the historical and newly entered data. The software is trained with a set of historical data from the Philippines' BFAR Region 1; and a set of test data are used to determine the forecast accuracy of the KNN technique. The DSS software is developed using Python as the programming language, Scikit-learn for implementing the KNN classifier, Anaconda as the Integrated Development Environment (IDE), Django as the web framework, AngularJS Chart for the interactive graphs and charts, MySQL for the database and Bootstrap as the front-end framework.



**Figure 1:** System Architecture of Web-based DSS for Water Quality Monitoring and Prediction of Outdoor Microalgae Cultivation

Figure 1 above shows the system architecture. Current water quality parameters (salinity, temperature) are entered into the system, and will be treated as the query. The parameters in the query will be stored in the historical data then will be extracted and cleansed to use in interpreting and checking the facts to produce the output modelled through graphs and charts. The model created together with the historical data will be analyzed by the inference engine to check rules in order to predict future water quality parameters of the outdoor microalgae cultivation.

### 3.2 Statistical Treatment

On the first phase of the study, the researchers gathered the data of outdoor microalgae water quality parameters in BFAR- Region 1 for the year 2015. The training data used for the prediction of the future water quality parameters was the data of Tank 1 and Tank 2 of the year 2015 while the testing data used was the data of Tank 3 of the year 2015. An aquatic expert was selected to help in determining the actual type of water that is being added for each scenario. Mean Absolute Percentage Error (MAPE) was used to compute the forecast error needed in computing the forecast accuracy of the DSS. To compute the forecast accuracy:

$$FA = 100\% - FE$$

Where: FA – Forecast Accuracy

FE – Forecast Error

The two-tailed test was used in computing the significant difference of the suggested type of water to be added by the DSS and by the aquatic experts.

### III. Findings and Discussion

Table 1 shows the total absolute percentage error of the web-based DSS in predicting the future water salinity and temperature of outdoor microalgae.

**Table 1:** Total Absolute Percentage Error per quarter for the year 2015

Water Quality Parameter	1 <sup>st</sup> Quarter	2 <sup>nd</sup> Quarter	3 <sup>rd</sup> Quarter	4 <sup>th</sup> Quarter
Temperature	3%	2.3%	2.4%	2.1%
Salinity	1.6%	1.3%	1.6%	1.1%

In Table 1, the temperature and salinity in the first quarter has a 3% and 1.6% of error respectively; in the second quarter the temperature and salinity has a 2.3% and 1.3% of error respectively; in the third quarter the temperature and salinity has a 2.4% and 1.6% of error respectively; and in the fourth quarter the temperature and salinity has a 2.1% error and 1.1% error respectively.

**Table 2:** Mean Absolute Percentage Error per quarter for the year 2015

Water Quality Parameter	1 <sup>st</sup> Quarter	2 <sup>nd</sup> Quarter	3 <sup>rd</sup> Quarter	4 <sup>th</sup> Quarter
Temperature	3.4%	2.9%	2.8%	3%
Salinity	1.8%	1.6%	1.8%	1.5%

In Table 2, the temperature and salinity for the first quarter has a 3.4% and 1.8% of error respectively; in the second quarter the temperature and salinity is 2.9% and 1.6% of error respectively; in the third quarter the

temperature and salinity has a 2.8% and 1.8% of error respectively; in the fourth quarter the temperature and salinity has a 3% and 1.5% of error respectively.

The percentage error in Table 2 was treated as forecast error which was needed to compute the forecast accuracy. Table 3 shows the forecast accuracy of the web-based DSS in predicting the future water quality level of Tank 3 quarterly.

**Table 3: Quarterly Average Forecast Accuracy of the Web-based DSS**

Water Quality Parameter	1 <sup>st</sup> Quarter	2 <sup>nd</sup> Quarter	3 <sup>rd</sup> Quarter	4 <sup>th</sup> Quarter	Average
Temperature	96.6%	97.1%	97.2%	97.2%	97.0%
Salinity	98.2%	98.4%	98.2%	98.7%	98.5%

In Table 3, forecast for temperature is 96.6% accurate and salinity is 98.2% accurate for the first quarter; for the second quarter, the forecast accuracy rate of temperature and salinity is 97.1% and 98.4% respectively; for the third quarter, the forecast accuracy rate of temperature and salinity is 97.2% and 98.2% respectively; in the fourth quarter, the forecast accuracy rate of the temperature and salinity is 97.2% and 98.7% respectively. The average forecast accuracy of the DSS in predicting the temperature and salinity is 97.0% and 98.5% respectively.

In computing the significant difference of the suggested type of water to be added by the DSS and by the aquatic experts, the two-tailed t-test was used on the data given by BFAR.

		Levene's Test for Equality of Variances				
		F	Sig.	t	df	Sig. (2-tailed)
WaterType	Equal variances assumed	.000	1.000	.000	642	1.000

**Figure 2:** Two-tailed t-test result of the significant difference of the suggested type of water to be added by the DSS and by the aquatic experts

From the generated result of independent t-test by IBM SPSS tool as shown in Figure 2, the significant table under the Lavene's Test for Equality column shows that the significance of both group (DSS and expert) is 1.000. The standard significance level is 0.05. Since the significance value is greater than 0.05 which means that the variability in the two conditions is about the same, it is concluded that there is no statistically significant difference between the suggested type of water to be added by the decision support system and by the aquatic experts.

#### IV. Conclusions

The DSS using the less powerful similarity-based classifier KNN has a high forecast accuracy rate in predicting the future water temperature and salinity of the outdoor microalgae. This could probably because of the small variances in the values of salinity and temperature data of outdoor microalgae tanks water. It is recommended to use cross-validation on the entire historical data instead of the hold-out technique were two-thirds (2/3) of the data are used for training and one-thirds (1/3) of the data were used for testing. Also, since the test data used were limited to a single year (2015), there could be no outlier that could affect the accuracy of prediction. Since the prediction accuracy for outdoor microalgae water quality status is high, the prediction software can be used and adopted by outdoor microalgae cultivators. The accuracy rate and confidence level can still increase as more historical data (2 to 3 years) are fed into the system.

Data for pH, D.O., and evaporation rate should be gathered; and retrain the system to consider these parameters in predicting the future water quality parameters. Since the researchers failed to gather a significant amount of data on these water quality parameters from microalgae cultivators like BFAR, it is strongly recommended that microalgae producers and cultivators be diligent in collecting and recording these data, because though lesser in effect, they are also determinants of water quality for outdoor microalgae.

As manual collection and recording of data is tedious and prone to error, microalgae cultivators should invest in hardware technologies that could capture the water quality parameters data in real-time so that the training data and testing data will be readily available and not be prone to human error. Hence, these human errors in data collection and recording that could render the training and testing data to be dirty and biased, can be avoided. Since water quality measurement can be done real-time with the integration of multi-sensor device,

the web-based DSS can be converted into a mobile-based application for more flexibility, portability, and real-time early warning.

In addition, the data can be subjected to time-series analysis which is applicable for predicting numerical values based on single predictor. The model produced may be evaluated against the ANN-based model; and the best model may then be recommended.

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