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Predictive Modeling of pH in a Small-Scale Aquaponics System: Multi-Layer Perceptron (MLP) Regression, Support Vector Regression (SVR) and Random Forest Regression Models

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ABSTRACT

Aquaponics is a growing industry that combines intensive food production with waste-stream recycling and water conservation, offering alternative solutions to soil degradation and water scarcity. This technique can contribute to global food security but requires careful management. One of the key parameters in aquaponics is pH, which must be maintained to accommodate three different types of living organisms: fish, plants, and bacteria. In aquaponics systems, pH naturally decreases due to the nitrification process, making monitoring essential. To predict pH levels in a small-scale aquaponics system—consisting of three hydroponic techniques (DWC, media bed culture, and NFT) combined with a tilapia fish tank—three machine learning models were proposed in this study. The results showed that the random forest regressor model can predict pH fluctuations over 12 days with a root mean square error (RMSE) of 0.0260 and a mean squared error (MSE) of 0.0006. The random forest model outperformed the MLP regressor and SVR models in terms of accuracy, suitability, and prediction error. Predicting pH is crucial for the stability of an aquaponics system.

INTRODUCTION

Aquaponics is an integrated system that combines a recirculating aquaculture system (RAS) with hydroponics (soil-less agriculture), where plant nutrients are provided by organic fish waste, with the assistance of nitrifying bacteria. The benefits of aquaponics are primarily its efficient use of resources. It contributes to water conservation by reducing water consumption by up to 90% compared to traditional agriculture **(Rharrhour *et al.*, 2022)** and minimizes chemical use since fish waste serves as the main source of nutrients for plants. These quasi-closed systems offer a sustainable method of food production with significant potential to contribute to global food security **(Rharrhour *et al.*, 2024)**. They can also provide local food self-sufficiency, as they can be set up in virtually any location.

Maintaining water quality is the biggest challenge that faces aquaponics systems. Given the fact that water is the matrix of nutrients exchange between aquaculture unit and hydroponic unit, water physicochemical parameters variation can impact positively or negatively this ecosystem's biocenosis. pH is one of the important water parameters in aquaponics, it plays a crucial role in these systems by affecting the health and growth of both fish and plants and the efficiency of nitrifying bacteria. Fish, plants and bacteria share generally the same tolerance ranges for water parameters **(Sommervile, *et al*., 2014)** while their pH optimal ranges are different **(Yep & Zheng, 2019)**. In general, for optimal plant growth, an acid pH is recommended **(Bugbee, 2004)** whilst nitrifying bacteria prefer neutral ranges **(Goddek et al., 2015)**. Fish optimal pH range varies depending on fish species, in general, RAS systems maintain pH between 7.0 and 8.0 **(Lennard & Goddek, 2019)**. Therefore, a neutral pH range of 7-9 is recommended for aquaponic systems **(Rharrhour *et al*., 2022)**.

Over time, pH in aquaponic systems naturally drops due to nitrification process **(Lennard & Goddek, 2019)**; the conversion of fish waste ammonia to nitrate results in hydrogen ions production, which makes monitoring and adjustment of pH a necessity. Research in aquaponics water quality has shown that a decrease of pH impact negatively the well-being of fish, plants and bacteria, while an increase of pH leads to a decrease of phosphorus availability **(Mori *et al.*, 2021)**; results have proven significant correlations between pH and other water quality parameters **(Rharrhour *et al*., 2024)**.

In a nutshell, pH balance is very crucial in aquaponics for the proper conditions meeting the fish, plants, and bacteria need. Regular testing of pH and slight adjustments will make the system increasingly stable and productive. The main objective of this research was to predict pH in two environments (i.e. hydroponics unit and fish tank) using three machine learning supervized regression models: The multi-layer perceptron, random forest, support vector based on a small-scale aquaponic system.

MATERIALS AND METHODS

1. Experimental design

This experiment was conducted to predict variation of pH values in a small-scale closed-loop aquaponics system. The present aquaponics systems were monitored over a period of 8 weeks in BIOECOGEN laboratory of the Faculty of Sciences of Rabat, MED V University.

2. Materials

- **Fish**: The Nile tilapia (*Oreochromis niloticus*) specimens were selected for the experiment, with an initial stocking density of forty-six juveniles with an initial average weight of 4.48g and an average length of 6.5cm.
- **Plants**: In this experiment, we chose to grow four species of leafy vegetables: sweet basil (*Ocimum basilicum*), two lettuce (*Lactuca sativa*) varieties (madrilene and sucrine), spinach (*Spinacia oleracea*) (Viroflay) and cabbage (*brassica oleracea*) (Copenhagen Market). The seeds of these plants were bought from local market, cultivated in potting soil ten (10) days before transplantation to the hydroponic unit using plastic net cup pots.

- **Aquaponics systems**: The system consisted of a square glass aquarium (48 × 51 × 53cm, L, W, H) fish tank filled with 71L of water, 3 plastic basins of 35cm long, 25cm wide, and 22.5cm high, each with an area of $0.0875m^2$ and a volume of $0.02m^3$, one of them filled with volcanic gravel (Pozzolan) as the growing medium, the others were used as deep water culture systems equipped each by an air pump of 3W and a maximum flow of $3.5l.min^{-1}$, 4'' PVC pipes and a submersible pump with an electrical power of 25W and a maximum flow rate of 1750 l/h for continuous water circulation between the fish tank and the grow bed. The aquarium was equipped with a heater of 300W, two mechanical internal filters and an air pump with an electrical power of 3W and a maximum flow of $3.5l.min^{-1}$.
- **Water quality testing**: Water parameters such as pH, temperature, total dissolved solids (TDS), and electrical conductivity (EC) values were measured daily using a multiparameter instrument "Hanna HI9814". Salinity was estimated from conductivity and temperature using the formula of **Aminot and Kérouel (2004)**.
- **Fish feed**: The fish were fed once-daily a commercial floating pellet feed made up of 37% crude protein; the feed was hand-delivered at a ratio of 2% of the total fish weight.

3. Methods

3.1. System setup

We adopted the fluid and drain system (Fig. 1), in which water was recirculated between the fish tank and grow beds in a continuous loop. Water was pumped from fish tank to a filtration system consisted of hand-made filter and biofilter, then flows into the hydroponic, while gravity takes the water back to the fish tank. We used a hand-made bell siphon in the media bed culture to ensure good oxygenation and water flow.

3.2. Fish feeding and growth monitoring

Fish were fed once a day at 2% of their body weight. The amount of feed was adjusted weekly based on the weight of the fish, which was measured every ten days. Fish were individually weighed using a digital balance (±0.01g accuracy).

3.3. Plant growth measurements

Plants were grown for 8 weeks. Plant initial height and weight were measured, while daily height was recorded. At the end of the experiment, the plants were harvested, and the fresh weight (g) was measured for each plant.

Fig. 1. Sketch of aquaponic system used in experiment

3.4. Water quality monitoring

In addition to pH, water samples were taken daily to measure temperature, electrical conductivity, and total dissolved solids (TDS) levels using a portable multiparameter instrument “Hanna HI9814”. Salinity values were calculated automatically using the formula of **Aminot and Kérouel (2004)**. Table (1) provides the optimal ranges of the mentioned water quality parameters; fish parameters ranges were defined based on rearing tilapia as fish species in experiment, while the plant parameter ranges were established as general optimal ranges for growing four different plant species.

Table 1. Water quality parameters optimal ranges in aquaponics
(Rakocy *et al.*, 2006; Resh, 2012; Sommervile *et al.*, 2014; Goddek *et al.*, 2015)

	Temperature (°C)	pH	EC (ppt)	TDS (ppt)	Salinity (ppt)
For fish	22 - 28	6.5 – 7.5	0.5 - 2	200 - 2000	0.5 - 2
For plants	18 - 24	4.5 - 6	1 - 3	500 - 2000	0.5 – 2

3.5. Statistical analysis

There are several essential steps for implementing the models followed in this process. We began by collecting and preparing the data, then the dataset was split into a training set (80% of the data) and a testing set (20%). Afterward, the model's performance was evaluated using metrics on the testing dataset, in addition to generating predictions and visualizing the models' outputs in order to compare their performance.

The multi-layer perceptron (MLP) regressor: In the context of supervised learning, we employed this neural network model to make predictions, as it can determine how inputs influence the outputs. Neurons in the input layer are connected to those in the hidden layer, and each neuron in the hidden layer is linked to the output layer, as shown in Fig. (2).

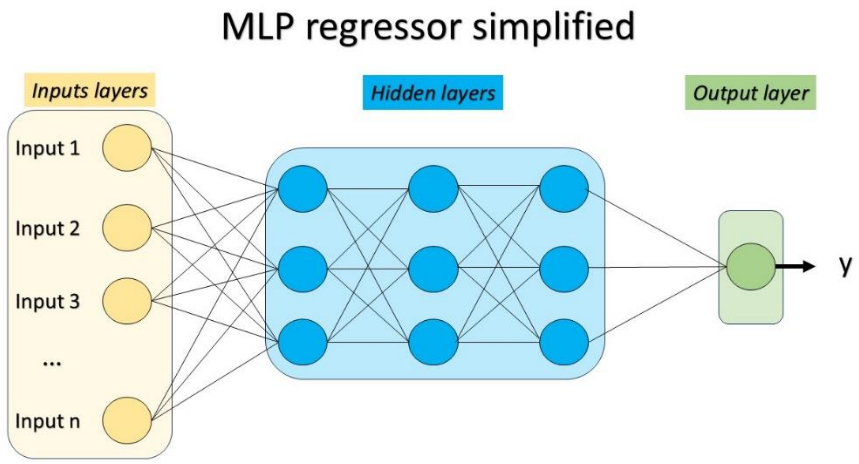


Fig. 2. Simplified schematic structure of the MLP regressor

In fact, the input layer transmits the input values to the neurons in the hidden layer, which compute weighted sums and apply activation functions. The output layer produces the final predictions, typically containing a single neuron that represents the predicted continuous value. The overall process in an MLP regressor relies on forward propagation and backpropagation. During forward propagation, the predicted vector of the MLP regressor model is generated.

$$\hat{y} = \sum w_{mn} x_n + B_m$$

Where, x_n is the input to the neuron coming from the previous layer; w_{mn} is the weight connecting the neuron to the neuron m; and b_m is the bias associated with the neuron m. To improve model performance and to quantify the error, we used the mean-squared error (MSE) as the cost function, which measures the deviation between the predicted output and the actual value z. For M total number of observations, the MSE is defined by:

$$MSE = \frac{1}{M} \sum (\widehat{z}_i - z_i)^2$$

When the error between the output value and the expected output is large, we proceed with backpropagation. This process involves adjusting the weights and biases using gradient descent, which determines the direction and magnitude by which the weights and biases need to be changed to minimize the error. The update is performed as follows:

$$w_{nm} \leftarrow w_{nm} - \eta \cdot \frac{\partial MSE}{\partial w_{nm}}$$

$$b_m \leftarrow b_m - \eta \cdot \frac{\partial MSE}{\partial b_m}$$

With η the rate learning which is the controller of the magnitude of change in that direction.

The random forest regressor creates multiple independent decision trees using a statistical technique called bootstrap sampling, which involves sampling with replacement from the original data to generate multiple subsamples corresponding to the trees. Each tree makes a prediction, and these predictions are then averaged to obtain the final prediction. This aggregation process helps stabilize the model by reducing the impact of random fluctuations captured by each tree, which in turn reduces the variance of the final model (Fig. 3).

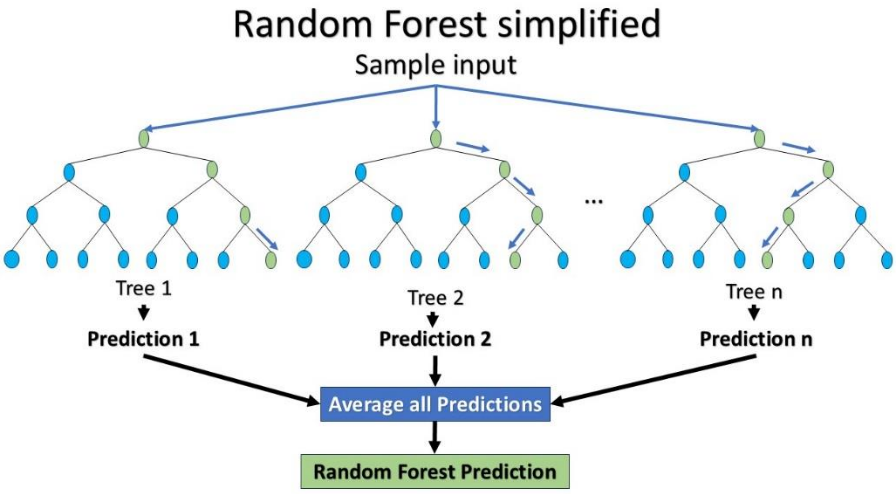


Fig. 3. Simplified schematic structure of the random forest regressor

For defining ^{n}trees as the total number of trees and $\hat{z}_i$ as the prediction of the i tree corresponding to the x observation, the subsequent formula was applied:

$$\hat{z}(x) = \frac{1}{n_{trees}} \sum_{i=1}^{n_{trees}} \hat{z}_i(x)$$

SVR (Support Vector Regression): it reposed on the margin ϵ is the selected area around the target function $f(x) = w^T.x + b$ in which w is the weight factor, furthermore ϵ is considered as tolerance for the error between f(x) and y the sample value. Errors are ignored within the margin ϵ, however the error is outside this margin, a penalty C is added to the cost function:

$$min_{wb} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*)$$

Where, ξ_i and ξ_i^* are the variables which measure the deviation of predictions outside the margin ϵ and C is the penalty coefficient.

For evaluating the performance and the effectiveness of these models, each model was evaluated based on the following evaluation indicators: Mean squared error (MSE), root mean squared error (RMSE) and mean absolute percentage error (MAPE) to assess its effectiveness and accuracy. The metrics were calculated as follows, where y_i is the true value, $\tilde{y}_i$ is the predicted value and N is the number of test samples:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \tilde{y}_i)^2$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \tilde{y}_i)^2}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \tilde{y}_i}{y_i}\right|$$

RESULTS AND DISCUSSION

1. Hydroponic unit

The density distributions of the water quality parameters measured in the hydroponic unit, along with the safe ranges for these variables and the percentage of data points within those ranges, are presented in Fig. (4). The results show that only temperature and pH had values outside the tolerance range for plant species, as defined in Table (1). Only 1.5% of the measured temperature values fell within the healthy range, with the water temperature in this experiment being set based on the fish species. pH values showed considerable fluctuations, with 12.1% of the values falling outside the safe range. For EC, TDS, and salinity, these parameters generally exhibit a strong correlation **(Rharrhour *et al*., 2024)**, which explains their similar fluctuations. Notably, 100% of the measured values for these parameters remained within the healthy ranges.

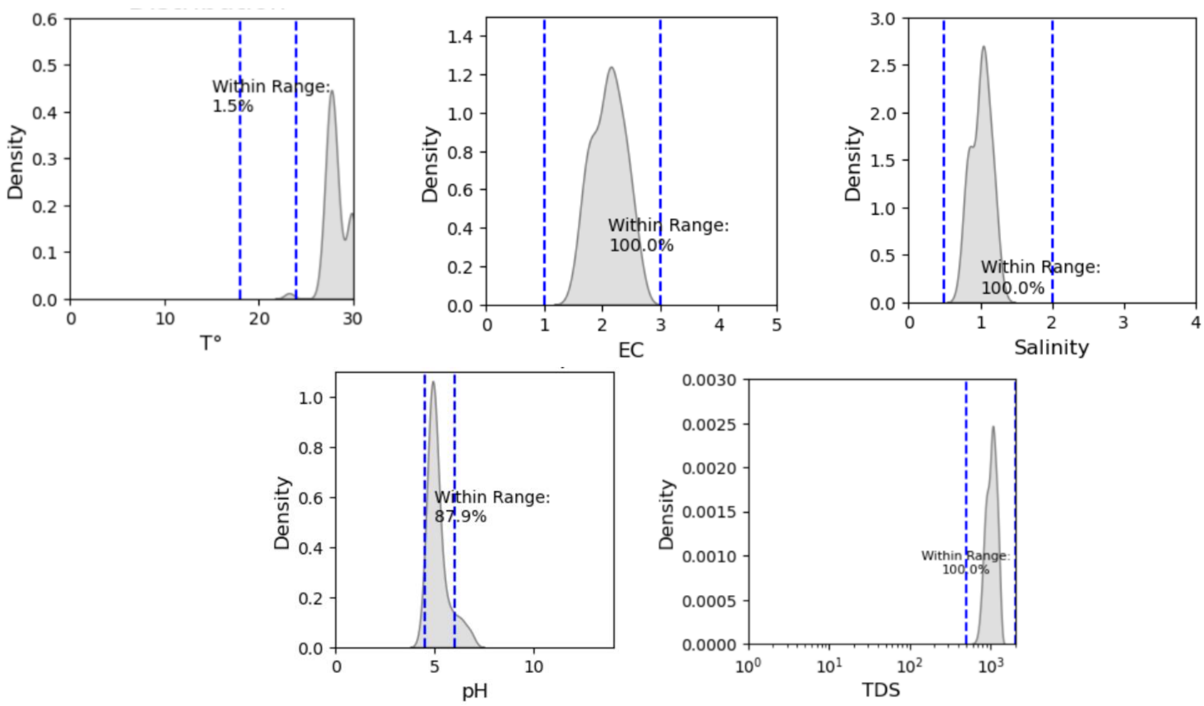


Fig. 4. Water quality parameters distribution in hydroponics unit

Density plots of daily measurement temperature “T°” (°C), electrical conductivity “EC” (ppt), salinity (ppt), pH, and total dissolved solids “TDS” (ppt), the upper and lower bounds for the safe range of each parameter are indicated with the vertical blue dashed lines.

Table (2) provides a summary of the descriptive analysis of water quality parameters in the hydroponic unit. The results reveal that the average pH in the hydroponic component is 5, with a standard deviation of 0.53. The standard deviation is slightly above 10% of the mean, which indicates weak deviation, suggesting that the pH values had low dispersion. As defined in Table (1), the pH values fall within the safe range for plants. Regarding temperature, the results show very weak dispersion of its values (with standard deviation < 10% of the mean), which can be explained, as mentioned earlier, by the use of a heater that helps maintain the temperature within the desired range. EC, TDS, and salinity showed considerable variations, but since these parameters are strongly correlated, their minimum and maximum values remained within the safe ranges for the plant species used in the experiment.

Table 2. Summary of descriptive analysis showing the mean and standard deviation (std) of water quality parameters in hydroponics unit

	pH	TDS	salinité	EC	T°
count	66.000000	67.000000	67.000000	67.000000	66.000000
mean	5.126364	1047.164179	1.007194	2.101343	28.143939
std	0.531215	141.462127	0.138434	0.280529	1.160654
min	4.440000	760.000000	0.710000	1.530000	23.200000
25%	4.817500	930.000000	0.890000	1.870000	27.500000
50%	4.930000	1060.000000	1.022000	2.120000	27.800000
75%	5.267500	1150.000000	1.109000	2.310000	28.775000
max	6.800000	1310.000000	1.307000	2.640000	30.000000

Several studies have investigated water quality in aquaponics, showing that water quality parameters exhibit significant correlations **(Rharrhour *et al.*, 2024)**. Fig. (5) provides a correlation matrix of water quality parameters. There is a strong positive correlation between electrical conductivity (EC), total dissolved solids (TDS), and salinity, which makes sense since TDS measures the total amount of dissolved solids in water, while EC indicates the ability of these dissolved solids to conduct electricity. On the other hand, salinity measures the ions that come from salts. Additionally, there is a negative relationship between pH and fish feed, which is logic since the conversion of fish waste ammonia to nitrate results in the production of hydrogen ions. Therefore, the more fish are fed, the more the pH drops. The main outcome of this analysis is the negative correlation between pH and fish feed. On the other hand, it has been shown that pH strongly correlates with phosphates **(Rharrhour *et al.*, 2024)**, being one of the limiting factors for plant growth. This explains the decreased growth observed in some lettuce heads at the end of the experiment.

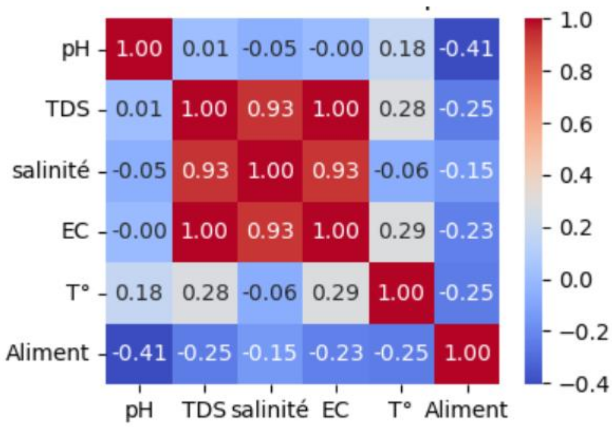
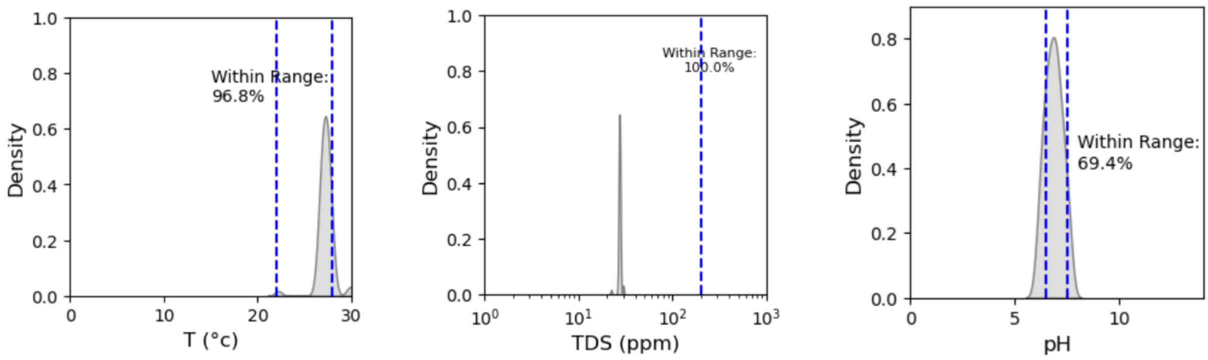


Fig. 5. Correlation matrix of water quality parameters in hydroponic unit

2. Aquaculture unit

Fig. (6) shows the density distribution of water quality parameters and their healthy ranges for the aquaculture unit. In the hydroponic unit, temperature and pH values were outside the healthy range. As mentioned earlier, the water temperature in this experiment was set according to the needs of the fish species (Tilapia), which explains why 96.8% of the temperature values fell within the healthy range. The use of a thermo-regulator helped maintain optimal temperature values for the aquaculture unit. Regarding pH, a significant percentage of values (30.6%) were outside the optimal range for tilapia. No additional chemicals were used for pH stabilization during the experiment, as the goal was to keep fish feed as the only input to the system. This explains the considerable variation observed in pH levels. TDS and EC values remained within the optimal ranges, unlike salinity, where 39.3% of the values were below 0.5ppt. At different times, temperature levels became too high for proper plant health, and pH levels dropped too low for fish health. Overall, however, this system meets the criteria for a healthy aquaponics system.



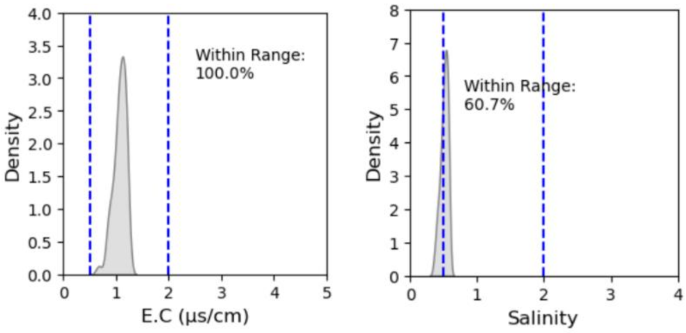


Fig. 6. Water quality parameters distribution in aquaculture unit

Density plots of daily measurement temperature “T°” (°C), total dissolved solids “TDS” (ppt), pH, electrical conductivity “EC” (ppt) and salinity (ppt). The upper and lower bounds for the safe range of each parameter are indicated with the vertical blue dashed lines

Summary of descriptive analysis of water quality parameters in aquaculture unit is provided in Table (3). Results revealed that the average pH in fish tank is 6.82 with a standard deviation of 0.40, meaning that pH values present a very weak dispersion (min = 6.04; max = 7.63). Temperature values are as well grouped around the mean ($\bar{x}$ = 27.32 °C; std = 0.61). EC, TDS and salinity standard deviations are slightly above 10% of the means, which reveal the weak dispersion of their values in the fish tank. In general, water quality descriptive analysis reveals that water in fish tank meets the criteria of healthy aquaponics system for tilapia.

Table 3. Summary of descriptive analysis showing the mean and standard deviation (std) of water quality parameters in aquaculture unit

	pH	T (°c)	E.C (ppt)	TDS (ppt)	Salinité (ppt)
count	61.000000	61.000000	61.000000	61.000000	61.000000
mean	6.825902	27.324590	1.071639	530.819672	0.505492
std	0.405230	0.618777	0.108185	55.925399	0.055834
min	6.040000	26.400000	0.820000	410.000000	0.365000
25%	6.510000	27.000000	1.010000	490.000000	0.468000
50%	6.820000	27.300000	1.080000	540.000000	0.512000
75%	7.090000	27.600000	1.160000	580.000000	0.551000
max	7.630000	30.000000	1.230000	610.000000	0.579000

The correlation matrix of water quality parameters in the fish tank is provided in Fig. (7). A strong relationship between electrical conductivity (EC), total dissolved solids (TDS), and salinity is evident in the figure. As for pH, this parameter shows a strong negative correlation with fish feed, EC, TDS, and salinity. As explained below, the more we feed the fish, the more excrement is produced, leading to increased mineralization, which causes a drop in pH. This, in turn, results in higher values of EC, TDS, and salinity. In contrast to the hydroponic unit, pH and temperature show a significant positive correlation in the fish tank. This explains why pH values fall below the safe range for the fish species.

Overall, however, the fish survival rate in this experiment was 100%, which demonstrates that this system operates within the parameters of a normal, healthy aquaponics system.

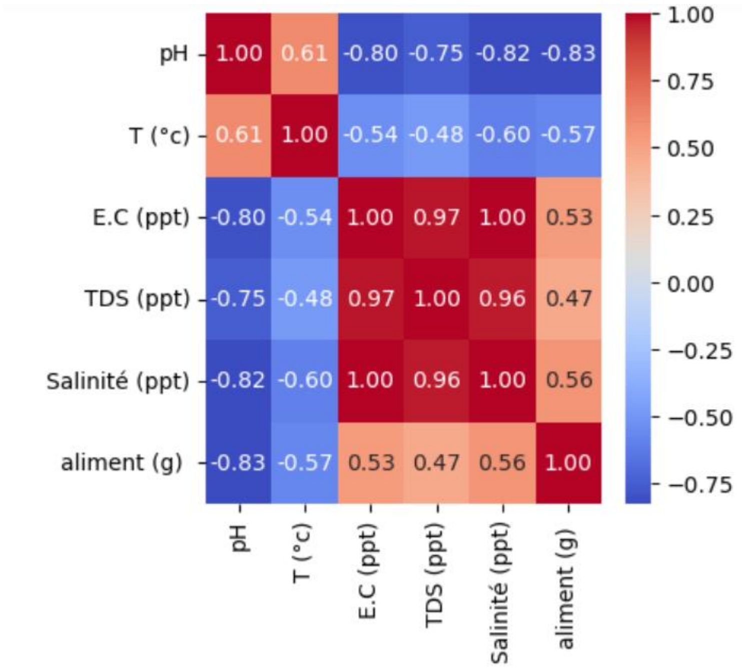


Fig. 7. Correlation matrix of water quality parameters in aquaculture unit

3. Simulation

To verify the correlations between water quality parameters and those affecting pH, for practical application in predicting pH variations, this paper established three models for comparative analysis: MLP regressor, random forest regressor, and SVR. These models were based on water quality data collected from this experiment. Tables (4, 5) present the evaluation metrics—RMSE, MSE, and MAPE—for the aquaculture and hydroponic units, respectively. The pH prediction results based on the three models are shown in Figs. (8, 9, 10). The dotted red curves represent the predicted pH values, while the blue curves indicate the measured pH values.

Table 4. Precision analysis of the prediction results for each model in aquaculture unit

Model	RMSE	MSE	MAPE
MLP Regressor	4.7179	22.2594	0.6933
Random Forest Regressor	0.0304	0.0009	0.0036
SVR	0.0604	0.0036	0.0066

Table 5. Precision analysis of the prediction results for each model in hydroponic unit

model	RMSE	MSE	MAPE
MLP Regressor	4.4109	19.4561	0.8836
Random Forest Regressor	0.0260	0.0006	0.0037
SVR	0.1215	0.0147	0.0134

As shown in Fig. (8), the predicted pH values from the MLP model differed considerably from the actual values. The evaluation metrics—RMSE, MSE, and MAPE—of the MLP model were 4.41, 19.45, and 0.88, respectively, for the hydroponic unit, and even higher for the fish tank, as shown in Table (5). These values indicate a high prediction error. Generally, we rely on the RMSE rather than the MSE to avoid canceling out positive and negative errors and to make model training easier. RMSE provides insight into the magnitude of the disparity between predictions and actual values.

On the other hand, MAPE represents the average absolute errors as a percentage of the actual values. As long as the percentage is low (less than 10%), the model's performance can be considered good.

For both the hydroponic and aquaculture units, we observed a significant difference between the actual and predicted values, with the predictions diverging from reality. This suggests that the model is underperforming, which can be explained by the small dataset used. The MLP model requires at least 1,000 data points to make accurate predictions. In this case, the model is overfitting, making it excessively sensitive to random fluctuations in the training data, which results in poor performance.

Support vector regression (SVR) has been widely adopted for both classification and regression tasks **(Taboada *et al.,* 2007)**. In this study, the SVR model achieved a balance between fitting the data and avoiding overfitting, which explains why the predicted pH values were closer to the actual values, as shown in Fig. (9).

The random forest model is another straightforward, non-parametric model that can be used for classification or regression tasks **(Rigatti, 2017)**. It uses randomization to create multiple decision trees, and the outputs of these trees are aggregated into a single prediction via voting. Both the SVR and random forest models showed low prediction errors, as indicated in Tables (4, 5).

When compared with the evaluation metrics of the SVR model, the random forest model's RMSE, MSE, and MAPE values for the hydroponic unit decreased by 78, 95, and 72%, respectively. For the fish tank, the random forest model’s RMSE, MSE, and MAPE values decreased by 49, 75, and 45%, respectively, compared to the SVR model’s evaluation metrics.

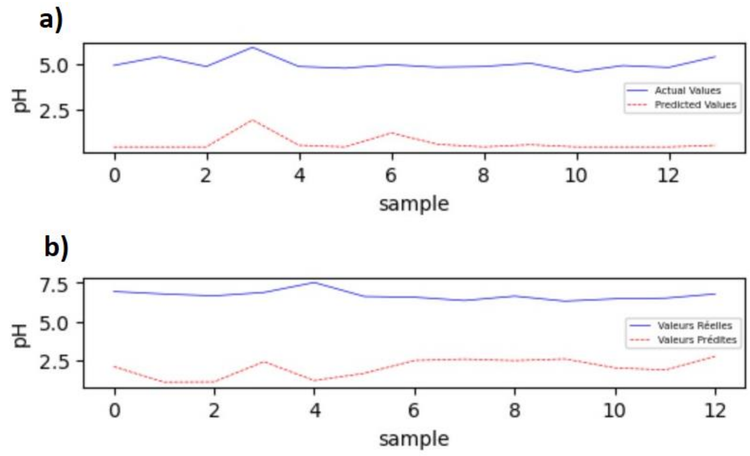


Fig. 8. pH prediction results based on MLP model for **a)** hydroponic unit and **b)** fish tank

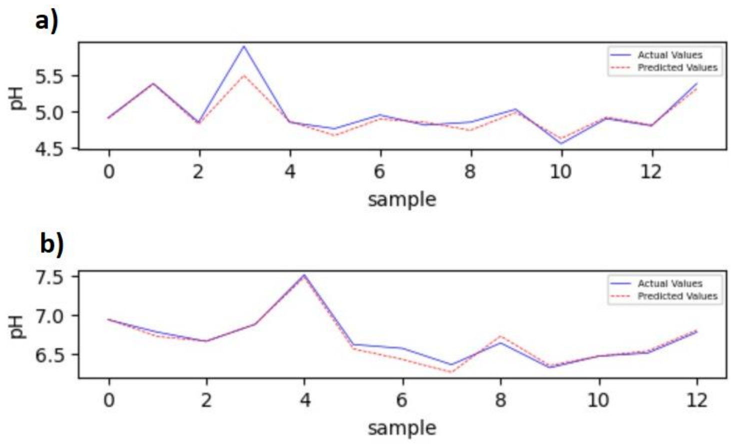


Fig. 3. pH prediction results based on SVR model for **a)** hydroponic unit and **b)** fish tank

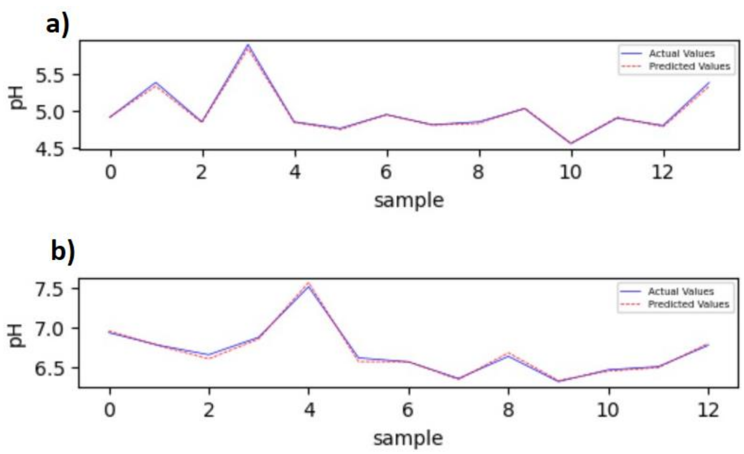


Fig. 4. pH prediction results based on random forest model for **a)** hydroponic unit and **b)** fish tank

Based on the analysis above, the random forest regressor model demonstrated higher prediction accuracy than the SVR and MLP regressor models. This is logic since random forest regressor is better suited for small datasets compared to other machine learning models or linear regression, which typically require larger sample sizes. However, when dealing with large datasets, random forest models may require more resources, such as memory and computational power, because they are generally more complex than linear regression models. As a result, other models may take longer to train compared to the random forest regressor.

CONCLUSION

Precise prediction of water quality parameters in aquaponics is essential for maintaining optimal and healthy conditions for the biocenosis. pH in an aquaponics system is significantly influenced by water quality, which is in turn affected by various physicochemical parameters. To address this issue, this paper proposed three machine learning models (MLP, SVR, and Random Forest) to predict fluctuations in pH values.

In aquaponics systems, pH is strongly related to factors such as fish feed, temperature, electrical conductivity, and other water quality parameters. In the aquaculture unit, the correlation coefficients for temperature, electrical conductivity, fish feed, and TDS were 0.61, -0.80, -0.83, and -0.75, respectively, all of which were higher than 0.3, indicating a strong correlation with pH. The pH prediction models developed in this study incorporate these strongly correlated environmental parameters. The predicted values from the random forest regressor model closely matched the true values, demonstrating a better fit compared to the other models. In contrast, the MLP model showed significant drawbacks, such as high prediction error and low precision.

The simulation results indicate that the RMSE of the proposed random forest model was 0.026, the MSE was 0.0006, and the MAPE was 0.0037 for the fish tank. When compared to the SVR and MLP models, the random forest model demonstrated advantages in terms of low prediction error, high accuracy, and a better ability to capture the nonlinear relationships between environmental factors and pH in an aquaponics system.

By accurately predicting pH, which directly impacts both fish and plant well-being in an aquaponics system, we can better understand pH trends and conditions. This provides a scientific basis for maintaining pH within healthy ranges, ultimately improving aquaponics productivity.

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