# Aquaculture Food Organism Quality Prediction using Transformer Network Approach

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***Abstract*—In the context of the evolution of automation and intelligence, deep learning and machine learning technology has widely applied in aquaculture in recent years, providing new opportunities for digital realization aquaculture. In this study, from four major indexes of water quality assessment, we applied machine learning algorithms and a novel deep learning techniques in smart fish aquaculture for the prediction of water quality parameters, base on the number of cells counting. Furthermore, the application of deep learning in in aquaculture are outlined, and the obtained results are analyzed. The experiment on an in-house data showed an extremely promising result on the application of artificial intelligence in aquaculture, helping to reduce costs and time as well as increase efficiency in the farming process.**

***Index Terms*—Aquaculture, artificial intelligence, deep learning, machine learning, transformer**

## I. Introduction

Aquaculture is defined as the cultivation (breeding, raising and harvesting) of aquatic organisms, especially for human food. This is an important industry with increasing importance in facing the problems of future food supply. According [1], this industry over the past four decades, has grown at an average rate of 7% per year, faster than other sectors in the animal food production field. This development is proportional to the increasing demand for fish of the world population which was estimated at 30 million tons each year base on the United Nations Food and Agriculture Organization. With such increasing capacity and productivity requirements, traditional aquaculture methods over time will lead to reveal disadvantages due to various factors. Shortage knowledge of aquaculture nutrition, food preparation, and proper feeding management will cause less desirability water quality both on land and off land farm due to accumulation of undigested food. For instance, poor water quality management leading to the imbalance of bacteria in the aquaculture environment that could affect to fish's disease resistant ability. Beside, Poor disease management, in part due to the slow identification of pathogens based on the number of plates in the laboratory, and thus improper use of drugs will lead to drug/chemical residues deposited in fish tissue. These problems not only lead to inefficiencies in quality control of seafood products, but also affect the health of consumers as well as cause associated economic losses. Therefore, the requirements for the application of artificial intelligence in this field are extremely necessary.

The idea of applying deep learning/machine learning in aquaculture was not novel in recent years. The applications of artificial intelligence on this field were conduct on studies related on fish biomass detection, identification and classification of fish, behavior analysis, and water quality parameter prediction. In 2016, Lorenzen et al [2] proposed fish production protection strategy that machine learning in fishery aquaculture offers new opportunities for intelligent aquaculture. Thus, their study showed that the combination of machine vision and machine learning can more accurately estimate the size, weight, numbers and other biological information of fish. Meanwhile, Monkman et al. [3] provided the R-CNN model under different architectures for the length estimation of European bass and applied OpenCV to measured and improved the accuracy. In the weight estimates problem, basing on the fish weight prediction, Researchers mainly do quality prediction based on the body shape characteristics of fish, and deploy the computer vision methods to extract fish size, fish back fish body shape and area to obtain quality assessment. Fernandes et al. [4] developed a model that applied the fusion of linear regression and CNN to estimate the weight by dividing the fish body path, which could achieve high prediction performance. Behavioral analysis is the work of estimated fish behavior, helping evaluated fish welfare, fishing and ecosystem [5]. There many conducted studies on fish feeding behavior, group behavior and abnormal behavior, etc. Water quality of an environment given by the water quality index. Therefore, monitoring water quality parameters of aquaculture environment in practice timing is important for the identification of biological anomalies in livestock production, disease prevention and corresponding risk reduction [6]. On this field, Zhang et al. [7] applied RNN for take advantages in processing time series and used it in dissolved oxygen monitoring systems for dissolved oxygen (DO) prediction task. In other aspects of innovation, Huan et al. [8] combine water quality information with weather information, apply GBDT method to choose factors that have a greater influence on dissolved oxygen and predict DO through the LSTM model.

Although the proposed methods solve many problems in aquaculture, especially water quality analysis. We find that food organisms base on water quality prediction has not received much attention. In the aquaculture industry, the development of artificial seed production technology is very important, and for this reason, the planned mass cultivation/management/feeding optimization of artificial seed feed organisms should be noticed. Therefore, the main purpose of this study is to propose a method of water quality analysis and prediction based on basic aquaculture parameters applying machine learning and Transformer network. From solving this problem, we expect to be able to facilitate the control of feed flow in aquaculture.

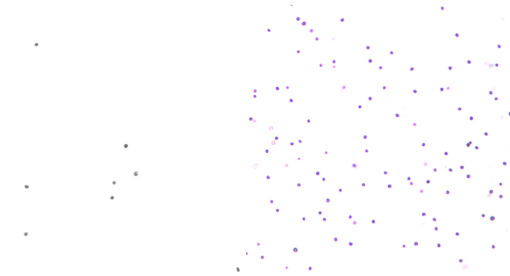
The remainder of this paper is organized as follows, we provide the materials and methods in section II. After that, in the section II-C, we will present our experimental results. Finally, we conclude and suggest some future work of our research.

## II. Materials and Methods

### A. Dataset and Challenges

We conducted our study on dataset provided on the '2021 Aquaculture Artificial Intelligence Model Contest' - the challenge held on the 2021 AI learning data construction support project of the Ministry of Science and ICT and the AI Information Society Promotion Agency, for university students or job-seeking students nationwide. With the motivation is stable mass feeding management of food organisms is importance of artificial seed culture industry, this challenges aiming to solves some problems that cause serious economic loss in the aquaculture artificial seed production industry such as: the reduction of aquaculture food organisms (plankton), difficulties in managing mass culture/feeding of food organisms, mass mortality in the process of seed production and the decreasing utilization of food organisms by field. In challenge, We are allowed to define the problem by ourselves, propose solutions within the provided data (free topic).

The obtained data from this challenge includes two types of data: the sensor data contains the information for Dissolved oxygen (DO), pH, salinity, Turbidity (NTU) from two places Goseong and Ilhae in 21 days and the images data shows the presentation of microscopy (Figure 1). Dissolved oxygen (DO) is the amount of oxygen in the aquatic environment that is accessible to fish, invertebrates and all living things in the water. DO in water is generated by the dissolution of air and a small part by photosynthesis of algae, etc. When the concentration of DO becomes too low, it will lead to respiratory difficulty, reduced activity in the water bodies, aquatic animals and can be deadly. The concentration of DO in nature ranges from 8-10ppm. This fluctuation depends on temperature, chemical decomposition and some other factors. DO is also an important indicator in assessing water pollution in the hydropower industry. In water quality measurement, pHs shows how acidic/basic water is. The range goes from 0 to 14, with 7 being neutral while pHs of less than 7 indicate acidity, whereas a pH of greater than 7 indicates a base. Salinity is the measure of the amount of dissolved salts in water. High levels of salinity in water with poor health or death of native vegetation, leading to loss of biodiversity through the dominance of salt-tolerant species, have the potential to alter ecosystem structure. Nephro Turbidity Unit (NTU), which has many variations, is an important parameter of water quality. The greater the scattering of light, the higher the opacity. A low turbidity value indicates high water clarity; High value indicates low water clarity. Beside, We applied cell detection basing Computer Vision Techniques for counting the number of microscopy. This value was considered as the target label on our study.



(a) Sample of Ilhae area (b) Sample of Goseong area

Fig. 1: Aquaculture dataset: microscopy samples on each area.

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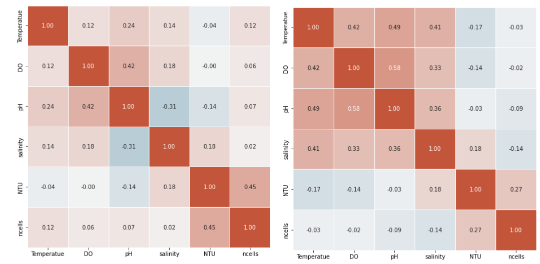


(a) Ilhae area (b) Goseong area

Fig. 2: Correlation matrix of two areas.

During the survey of this dataset, we analyzed the distribution of microscopy, the variation of measurement values over time. Besides, we also analyze the correlation of measurement values with each other and with the microcopy number (Figure 2). From the available analysis, we find that the data in Goseong is abundant and better distributed while the data at Ilhae seems to be more difficult to use for training. Therefore, we decided to use the data in Goseong for training progress while the data of Ilhae was considered as tet set.

### B. Proposed method

*1) Overview:* In this project, we proposed the system that predict the microscopy counting of water from data sensors for controlling the water quality basing on both traditional machine learning and deep learning models. The developments of artificial intelligence (AI) facilitated the integration of the principles of machine learning and deep learning into real-world applications. Based on these conditions, we aim to design an intelligent program that can replace complex measurement and calculation processes and are easily influenced by external factors. From the measurement indexes of aquaculture on samples of water (pH, sanlinity, NTU, DO,

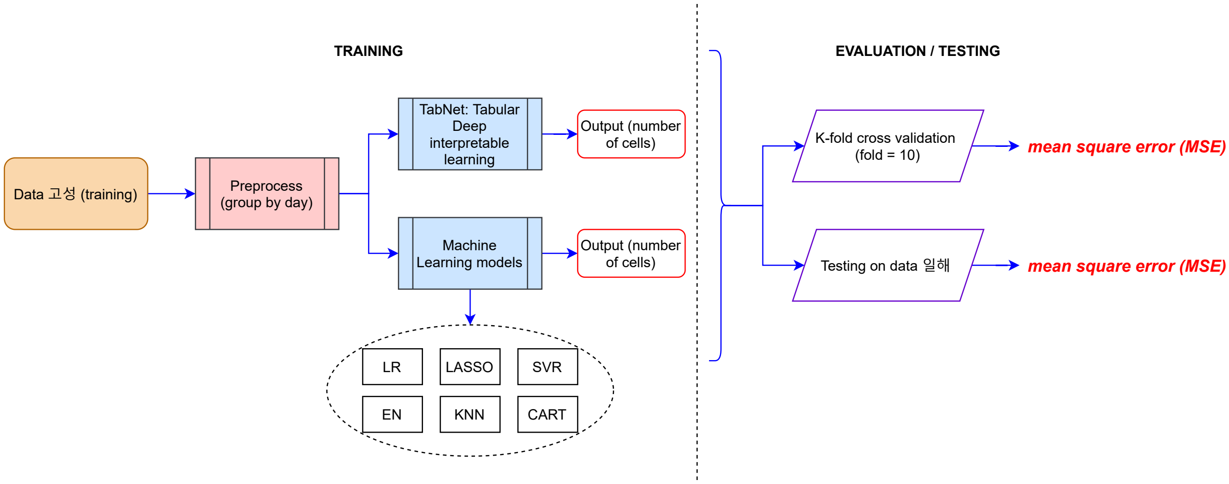


Fig. 3: The overall framework for number microscopy prediction.

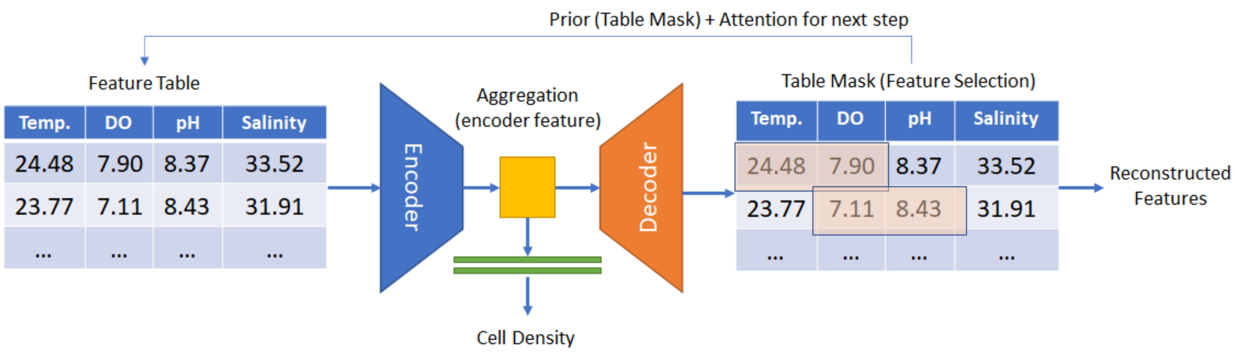


Fig. 4: TabNet model implemented on the system.

temperature), we predict the number of cells on these samples. This allows us to control the feeding dose in aquaculture with the least amount of effort and time. Collaborated with modern, high performance computer and hardware devices, machine learning technology can exploit the multi dimensional features and depth information in the data.

Overall, we could frame this problem as supervised learning problem where we will you different regression models to learn the relationships within the provided aquaculture measurement indexes and predict the total number of microscopy in water.

*2) Model Architecture:* The overall of our study pipeline for this task was illustrated as Figure 3. As we mentioned above, Based on our observations, the data from the Goseong area is abundant, balanced as well as less noisy, so we conduct training progress on this set. Before feeding the data into the regression models, we group the samples by the day, the measurement indexes values of each day will be calculated by the mean of all measurement time on that day. For the models, we use 6 classic algorithms of regression problem include: Linear regression (LN), Lasso regression (LASSO), support vector regression (SVR), Elastic-Net regression (EN), K Nearest Neighbors regression (KNN) and Classification and Regression Trees (CART). Beside, we apply TabNet [9] - a novel deep learning method basing on attention transformer for tabular learning on the same task.

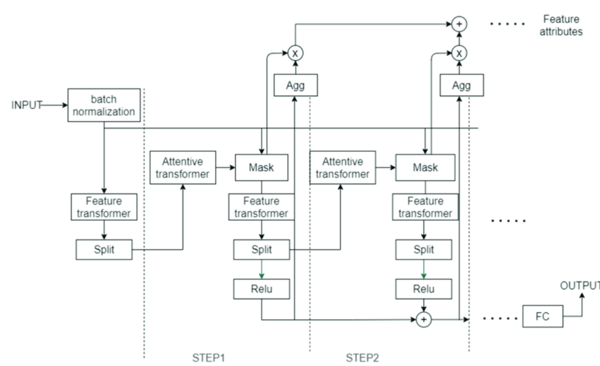


Fig. 5: TabNet architect.

### C. TabNet model:

TabNet [9] is trained basing on gradient descent-based optimization, allowing for flexible integration into the end-to-end learning process. Sequence attention is applied to the instance-wise features selection at each decision step for better interpretability and learning as the learning capacity isused for

TABLE I: Comparison between the proposed method (TabNet) with baseline machine learning models

| | **Goseong** | | **Ilhae** | |
|---|---|---|---|---|
| **Method** | **MAPE** | **MSE** | **MAPE** | **MSE** |
| Linear Regression (LR) | 0.591 | 4625 | 1.243 | 8232 |
| Lasso Regresson (LASSO) | 0.599 | 4402 | 1.242 | 8150 |
| Elastic-Net regression (EN) | 0.586 | 3850 | 1.141 | 7323 |
| K Nearest Neighbour (KNN) | 0.554 | 3601 | 1.010 | 8281 |
| Classification and Regression Trees (CART) | 0.520 | 4816 | 1.118 | 10788 |
| Super vector regression (SVR) | 0.629 | 4417 | 0.822 | 6916 |
| Our method using TabNet | **0.278** | **1057** | **0.397** | **2834** |

the most helpful features. In addition, a single deep learning engine is utilized for feature selection and reasoning. The architecture of Tabnet is presented at Figure 5. The detail of our implement for TabNet model on the data were show as Figure 4. The encoder stage of the model is built up by the feature transformer, feature masking, and the attentive transformer. The feature selection masks that contained the model's interpretable information are concatenated for obtaining the important features. In the encoder stage, feature transformer blocks are used at each step for feature reconstructing.

## III. Experimental results

On the evaluation process, we use K-fold validation, an effective tactic in preventing overfitting problems. From the obtained the prediction results from both K-fold validation on the training set and the test set. The evaluation metric used for all methods in this study is mean square error (MSE), calculated as:

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

In which, $N$ is the number of testing samples, $y_i$ is the prediction values and $\hat{y}_i$ is the ground truth. The lower error value, the better performance that model has. Beside, we also use mean absolute percentage error (MAPE), calculated as:

$$\mathrm{MAPE} = \frac{100\%}{N}\sum_{t=1}^{N}\left|\frac{\hat{y}_i - y_i}{\hat{y}_i}\right| \tag{2}$$

The absolute value in this ratio is summed for every prediction point in time and divided by the number of fitted points $N$.

The experimental results is showed at table I. The above results show that the performance of the overall methods in Goseong area is better than in Ilhae thanks to the better quality of data on Goseong area. It could be noticed that the attention base TabNet model outperform compare to the other machine learning base methods, obtained $0.287$ of MAPE and 1057 of MSE on Goseong set, showing a significantly improvement compare to the highest among machine models (CART with $0.520$ of MAPE and KNN with 3601 of MSE ). In the Ilhae set, our method also achieves the best results with $0.367$ of MAPE and $2834$ of MSE. The combination of tree base and interpretable learning takes advantage from the robustness features on training process.

## IV. Conclusions

In this paper, we presented a novel deep learning method implemented for aquaculture food organism quality prediction that predict the microscopy counting of water from data sensors for controlling the water quality . The application of the attention tabular learning approach shows the potential improvement of the whole benchmark traditional machine learning systems. However, our system can be continued to evolve based on temporal context information that leverages interpretive sources from the past to predict future results. Based on that, our future goal is to extend the system by implementing other deep learning models and develop the system according time-series base.

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