A TabNet – Based System for Water Quality Prediction in Aquaculture

Trong–Nghia Nguyen[1], Soo Hyung Kim[1], Nhu–Tai Do[1], Thai–Thi Ngoc Hong[2], Hyung Jeong Yang[1], Guee Sang Lee[1]

Abstract

In the context of the evolution of automation and intelligence, deep learning and machine learning algorithms have been widely applied in aquaculture in recent years, providing new opportunities for the digital realization of aquaculture. Especially, water quality management deserves attention thanks to its importance to food organisms. In this study, we proposed an end–to–end deep learning–based TabNet model for water quality prediction. From major indexes of water quality assessment, we applied novel deep learning techniques and machine learning algorithms in innovative fish aquaculture to predict the number of water cells counting. Furthermore, the application of deep learning in aquaculture is outlined, and the obtained results are analyzed. The experiment on in–house data showed an optimistic impact on the application of artificial intelligence in aquaculture, helping to reduce costs and time and increase efficiency in the farming process.

Keywords : Aquaculture | Artificial Intelligence | TabNet | Water Quality | Deep Learning

I. INTRODUCTION

Aquaculture is defined as the cultivation of aquatic management, especially for human food. This is an essential industry with increasing importance in facing future food supply problems. Over the past four decades, this industry has grown at an average rate of 7% per year, faster than other sectors in the animal food production field [1]. This development is proportional to the increasing demand for fish of the world population, estimated at 30 million tons each year. With such increasing capacity and productivity requirements, traditional aquaculture methods will reveal disadvantages over time due to various factors. Shortage of knowledge of aquaculture nourishment, food provision, and proper supply operation will cause less desirability water quality both on land and off the land farm due to the redundancy of undigested food. Poor water quality management leads to the imbalance of bacteria in the aquaculture environment that could affect fish's disease–resistant ability. Besides, poor disease organization, partly 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 lead to inefficiencies in quality control of seafood products and affect the health of

1 Department of AI Convergence, Chonnam National University
2 Department of Economics, Chonnam National University
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Corresponding Author: Soo Hyung Kim e–mail: shkim@jnu.ac.kr

consumers and cause associated economic losses. Water quality plays a pivotal role in the grow-out organization and the well-being of aquaculture animals. Declining water characteristic can be directly fatal, but more important; it emphasizes aquatic animals that make them more suggestible to infectious infirmity [2]. However, in contrast, the viability and growing of aquatic creatures in the culture system are reduced due to the deterioration of water quality. Therefore, applying modern science and technology in general and artificial intelligence in particular in this field is essential.

The idea of applying deep learning/machine learning in aquaculture was not novel. Artificial intelligence applications in this field were conducted on 4 tasks: fish biomass detecting, behavior analysis, fish recognition and classification and water quality prediction. In 2016, Lorenzen et al. [3] proposed a fish production protection strategy that machine learning in fishery aquaculture creates advantages for smart aquaculture. Thus, their study showed that the concatenation of computer vision and machine learning could more effectively evaluate the size, weight, numbers, and other fish biological information. Meanwhile, authors in [4] provided the R-CNN system with dissimilar structures for the length calculation of bass and applied OpenCV to measure and improve the accuracy. In the weight estimates problem, based on the fish weight prediction, authors mainly conduct a quality predictions task based on the fish body shape characteristics and deploy the computer vision methods to extract fish size, fish back, body shape, and area for obtaining a quality assessment. Fernandes et al. [5] developed a model that applied the fusion of CNN and linear regression to estimate the weight by separating the fish body path, achieving high prediction performance. Behavioral analysis is the work of estimated fish behavior, helping evaluate fish welfare, fishing, and ecosystem [6]. Besides, many conducted studies on fish feeding and abnormal behavior, etc. The water quality index gives the water quality of an environment. Therefore, monitoring water quality parameters of the aquaculture environment in practice timing is essential for identifying biological anomalies in livestock production, disease prevention, and corresponding risk reduction [7]. In this field, Zhang on [8] applied RNN to take advantage of temporal data processing and used it in dissolved oxygen monitoring models for dissolved oxygen (DO) prediction tasks. Although the proposed methods tackle many aquaculture problems, especially water quality analysis, we find that food organisms based on water quality prediction have not received much attention. In the aquaculture industry, artificial seed production technology development is critical. For this reason, the planned mass cultivation/management and feeding optimization of synthetic seed feed organisms should be noticed. Therefore, the primary purpose of this study is to propose a method of water quality analysis and prediction based on basic aquaculture parameters applying machine learning and a Transformer [9] based network named TabNet [16]. We expect to facilitate feed flow control in aquaculture by solving this problem. We proposed an end-to-end AI system that analyzes, trains, and predicts water cell density to assess food organism quality from the sensor data containing major water quality features. Our main idea is to exploit the feature selection of five quality parameters based on deep learning techniques included on TabNet: transformer, table mask for feature extraction, and Auto-Encoder architect.

II. RELATED WORK

Previous studies on water quality prediction utilized traditional machine learning approaches and lacked robustness in high-dimensional data. This makes the models lack extension ability and makes them unable to fully deliberate the underlying features of big data [10]. Fortunately, recent years have seen a widespread application of deep learning models to water quality prediction. Chen et al. [11] proposed a prediction system based on PCA and LSTM. PCA was used as a features extraction model to generate the main influencing factors of dissolved oxygen in aquaculture, removing the correlation between the baseline variables and reducing the input vector dimension. The obtained features are then fed into LSTM as the input factor. Their model outperformed the recent methods such as Principal component analysis-Back propagation (PCA-BP), Principal component analysis-Least squares support vector machine (PCA-LSSVM), and LSTM in cases of the mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE), respectively. With the same purpose of Chen et al. [11], Li et al. [12] used SAE as the replacement for PCA in the features extraction task while LSTM is still used for the prediction process. Experimental results show that SAE achieves better efficiency with 0.0056, 0.0077, and 0.0242 for 3h, 6h, 12h prediction, respectively. These results showed a remarkable enhancement compared to LSTM, BPNN, and SAE-BPNN. In different views of innovation, Huan et al. [13] combine water quality features with weather characteristics, apply the GBDT approaches to choose factors that have a more significant influence on dissolved oxygen, and predict DO through the LSTM method. Otherwise, Yang et al. [14] developed a multiscale aquaculture water quality prediction system that leveraged the idea of combining complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and LSTM. In this study, CEEMDAN was used for stepwise decomposition of distinct water quality features at different timestamps to create a series of intrinsic mode function components (IMF) with the same characteristic scale. Fu et al. [15] used a temporal convolutional network (TCN) for the water quality prediction task to solve the long-term prediction issues and time-series data. Their model achieved higher results than RNN, BI-SRU, LSTM, and GRU with 91.91% accuracy and reduced the cost of training and prediction time by 64.92% and 7.24%, respectively. These impressive results open a promising future for the application of deep learning to aquaculture and provide an excellent impetus for this research.

III. PROPOSED METHOD

In this investigation, we proposed a system that predicts the cell counting of water from data sensors to control the water quality based on traditional machine learning and deep learning models. Artificial intelligence (AI) developments facilitated the integration of machine learning principles and deep learning into real-world applications. Based on these conditions, our purpose was to design an intelligent program that can replace complex measurement and calculation processes easily influenced by external factors. From the measurement indexes of aquaculture on water samples (pH, salinity, NTU, DO, 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 algorithms could exploit the multi-dimensional features and depth information in the data.

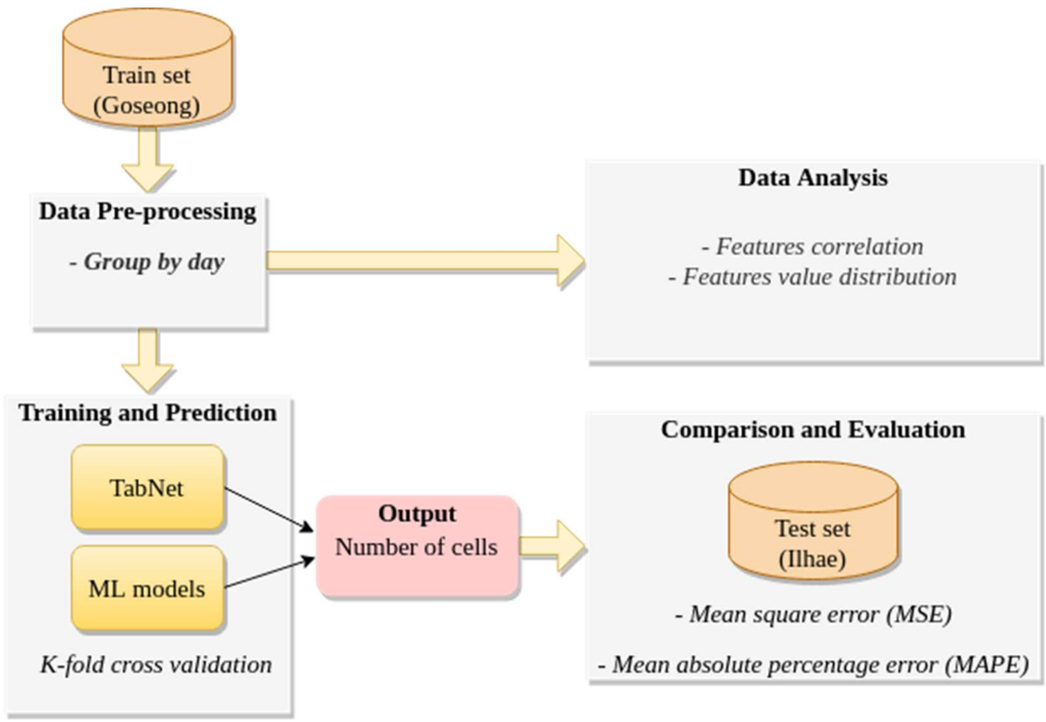


Figure 1. The overall framework of the proposed system. The system includes 3 main path: Data Analysis; Training and Prediction; Comparison and Evaluation.

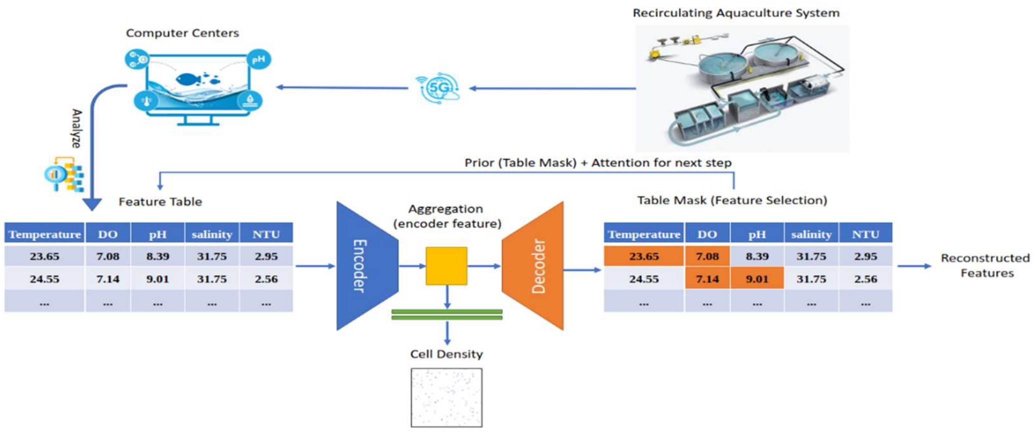


Figure 2. TabNet model implemented on the system.

3.1 Study pipeline

The overall of our study pipeline for this task is illustrated in Figure 1. We frame this problem as a supervised learning task. From the dataset containing 5 indexes of water samples, we aim to predict the total number of cells on each sample. Different regression models were applied to learn the relationships within the provided aquaculture measurement indexes and predict the total number of cells. Our experiment dataset is an in–house dataset collected from 2 places: Goseong and Ilhae. Based on our observations, the data from the Goseong area is abundant, balanced, and less noisy, so we first conduct training progress on this set. We group the samples by the day before feeding the data into the regression models. The measurement indexes values of each day will be calculated by the mean of all measurement time on that

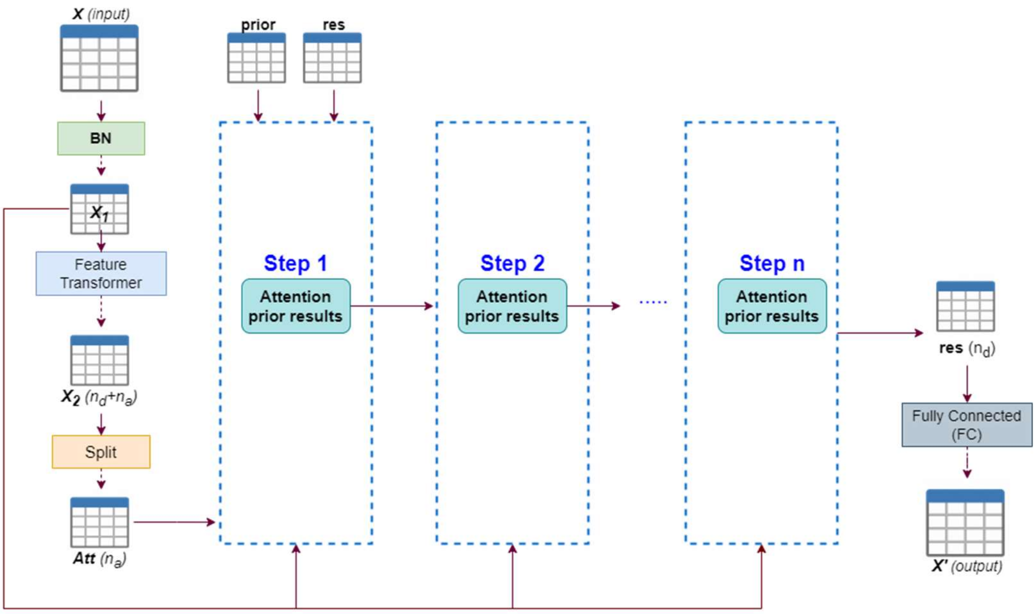


Figure 3. TabNet overall architecture.

day. For the models, we use 6 classic algorithms of regression problems include Linear regression (LN) [17], Lasso regression (LASSO) [18], support vector regression (SVR) [19], Elastic-Net regression (EN) [20], K Nearest Neighbors regression (KNN) [21], and Classification and Regression Trees (CART). Besides, we apply TabNet [16] – a novel deep learning method based on attention transformer for tabular learning on the same task

instance-wise features selection for better interpretability and used as the studying capacity for the most salient features. The overall architect of TabNet was proposed in Figure 3. The main paths of this model are Features Transformer Block with Gate Linear Unit layer (GLU), Decision Steps (DS), and Attentive Transformer in each Decision Step. Firstly, the raw tabular X data will be normalized by the Batch Normalization layer (BN) to produce X_1. In the next step, the normalized data go

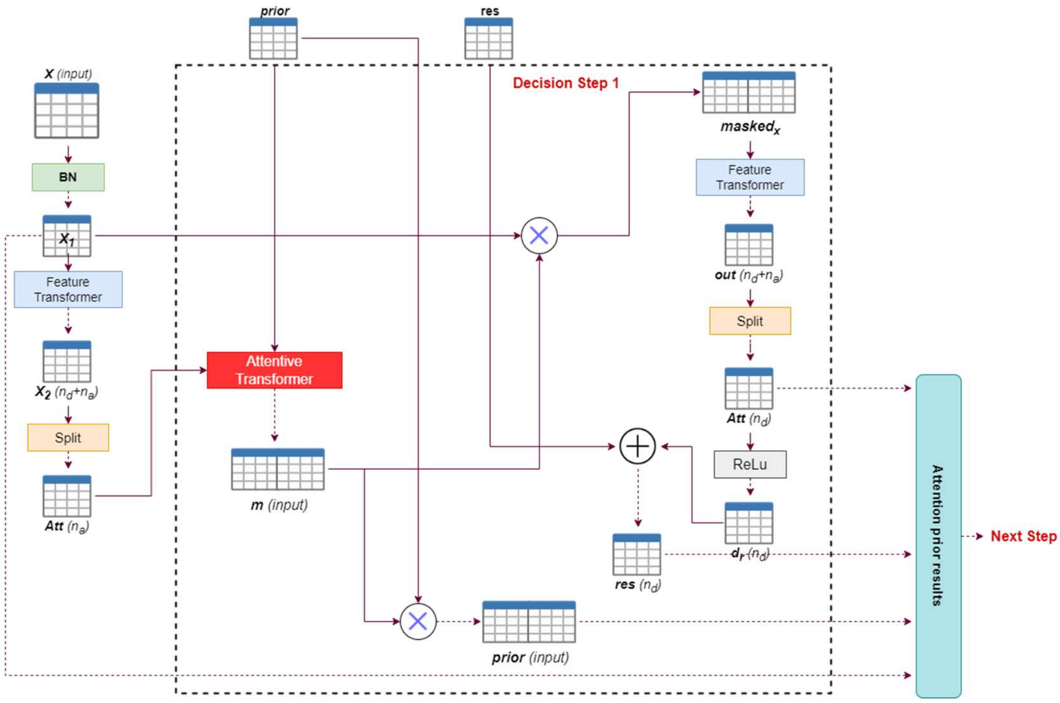


Figure 4. Process on each Decision step.

3.2 TabNet – Attention-based model for tabular learning

TabNet was proposed by Google researchers in 2020. Its main idea was based on decision trees and interpretable learning for taking advantage of efficient features. In which, for each decision step, the sequential attention was applied to

through the Feature Transformer (FT) for getting X_2. The transformed feature was divided into 2 paths: 1 has the size of the decision layer n_d and 1 has the size of the attention bottleneck n_a. The n_a size path was selected as the input of the Attentive Transformer on the Decision Step (Figure 4), integrated with the prior for producing the attention mask m. The attention mask was used for both updating the prior in the next Decision Step and accomplishing the attention mechanism by multiplying with normalized data X_1 for getting masked data x. x go through FT + Split + ReLu layers and concatenate with initialized *res* data to achieve result shape data *res*(n_d).

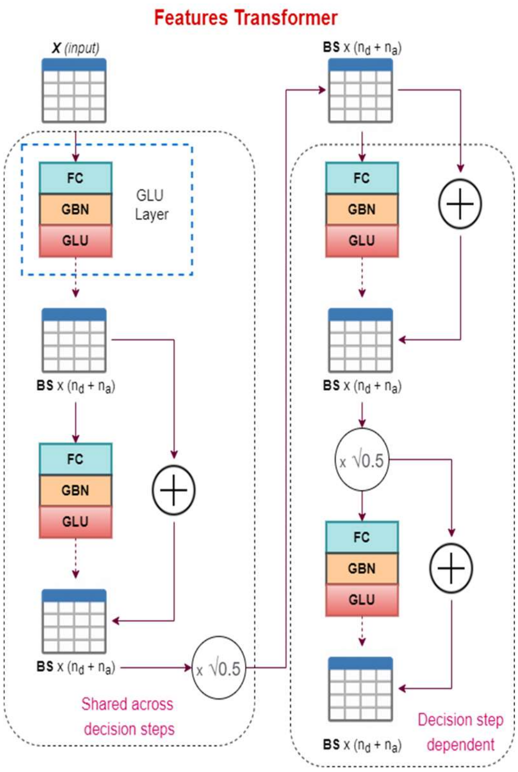


Figure 5. Feature Transformer. *input*: shape of input data; BS: Batch size; n_d: size of the decision layer; n_a: size of the attention bottleneck.

3.2.1 Feature Transformer (FT) and GLU

According to Figure 5, the Feature Transformer block (FT) contains 4 GLU layers. Each GLU layer includes a Fully Connected Layer (FC), a Ghost Batch Normalization (GBN), and GLU. The main purpose of the GLU layers was to split the size *input* of the input data into the tensor size $n_d + n_a$. In which, the FC layer will be mapping *input* to $2(n_d + n_a)$ while the GBN halves the shape into the final value $n_d + n_a$. In the Feature Transformer, the first 2 GLU layers were shared across the entire network. The weights of their elemental FCs are initialized only once, and these values will be shared for any future FT blocks. Otherwise, the last 2 are different for each FT, allowing for more flexible modeling. Besides, instead of multiplying like ResNet, these GLU layers are concatenated together.

3.2.2 Attentive Transformer

For integrating the attention mechanism to the network, Attentive Transformer (ATT), presented in Figure 6, was applied by forcing sparseness into the feature set and studying to concentrate only on individual variables. A Fully Connected layer will undertake the training process by spreading the tensor size n_a to the values of *input*. Finally, *Sparsemax* – an alternative of *Softmax* will be used in order to push any probability lower than a particular threshold to zero.

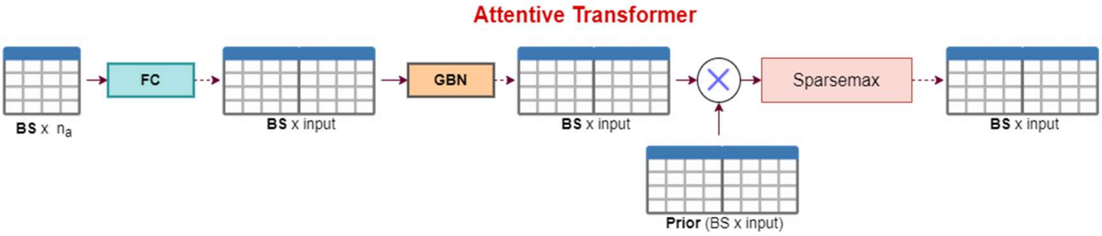
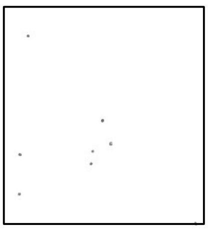


Figure 6. Attentive Transformer.

IV. EXPERIMENT AND RESULTS

4.1 Aquaculture Dataset

We conducted our study on the dataset provided on the '2021 Aquaculture Artificial Intelligence Model Contest' – the challenge held on 2021 AI learning data construction support project of the Ministry of Science and ICT and the AI Information Society Promotion Agency university students or job-seeking students nationwide. With the motivation is stable mass feeding management of food organisms is the importance of artificial seed culture industry, this challenge aiming to solves some problems that cause severe 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 the 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 temperature, Dissolved Oxygen (DO), pH, salinity, Turbidity (NTU), and temperature from two places, Goseong and Ilhae, in 21 days, and the images data shows the presence of microscopy. 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 [22]. 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/essential water is [23]. The range


(a) Sample in Ilhae

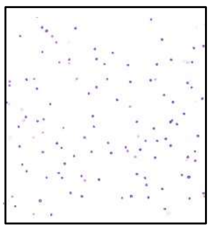

(b) Sample in Goseong

Figure 7. Microscopy image sample on 2

goes from 0 to 14, with 7 being neutral while pHs less than 7 indicate acidity, whereas a pH greater than 7 indicates a base. Salinity is the measure of the number 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 [24]. Nephelometric Turbidity Unit (NTU), which has many variations, is an essential water quality parameter [25]. The greater the scattering of light, the higher the opacity. A low turbidity value indicates high water clarity; a high value indicates intense water clarity. Temperature plays a key role in water quality assessment [26]. It directly determines which organisms, from plankton to fish, can live in the lake and where they thrive. Besides, we applied cell detection basing Computer Vision Techniques for counting the number of microscopies. This value was considered as the ground truth in our study.

4.2 Results and Discussion

On the evaluation process, we conduct our experiment on two sets: Ilhae and Goseong. It should be noticed that the data in Goseong is more abundant (Figure 7). In detail, each set contains the measurement information of water samples on 21 days. The Ilhae set includes 122,170 samples while the Goseong set contains a total of 123,818 samples. For each set, we use 5−folds cross−validation and report the mean evaluation score over 5−folds. The evaluation metric used for all methods in this study is mean square error (MSE), calculated as:

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

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

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

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

Table 1. Comparison results between proposed TabNet with baseline machine

	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**

points N.

The experimental results are shown in Table 1. The above results show that the performance of the overall methods in the Goseong area is better than in Ilhae, thanks to the difference in data quality on the Goseong area. Our proposed TabNet model (MAPE: 0.278; MSE: 1057) outperformed LR (MAPE: 0.591; MSE: 4402), LASSO (MAPE: 0.599; MSE: 4402), EN (MAPE: 0.586; MSE: 3850), KNN (MAPE: 0.554; MSE: 3601), CART (MAPE: 0.520; MSE: 4816) and SVR (MAPE: 0.629; MSE: 4417) for the Goseong set. In terms of Ilhae set, our approach achieved 0.397 of MAPE and 2834 of MSE, drastically reducing up to 0.843 of MAPE and 7954 of MSE compared to other methods. The reason for these impressive results was the combination of tree base and interpretable learning takes advantage of the robustness features of the training process. The obtained results are the foundation for us to deploy the end-to-end AI system for the mentioned challenge. The training, analysis, and prediction demo are illustrated in Figures 8, 9, and 10, respectively.

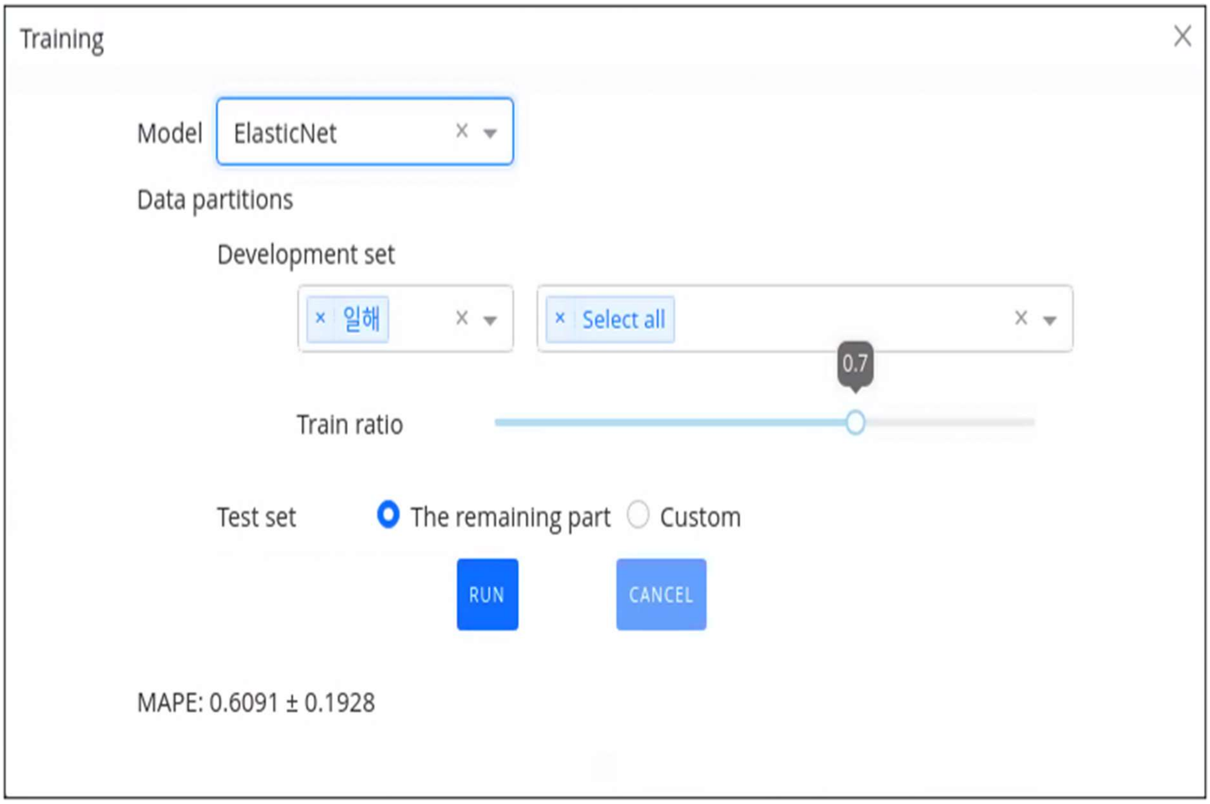


Figure 8. Training Demo includes option for: model selection (TabNet and 6 ML models); dataset for training (Goseong or Ilhae); train ratio and customization for test set.

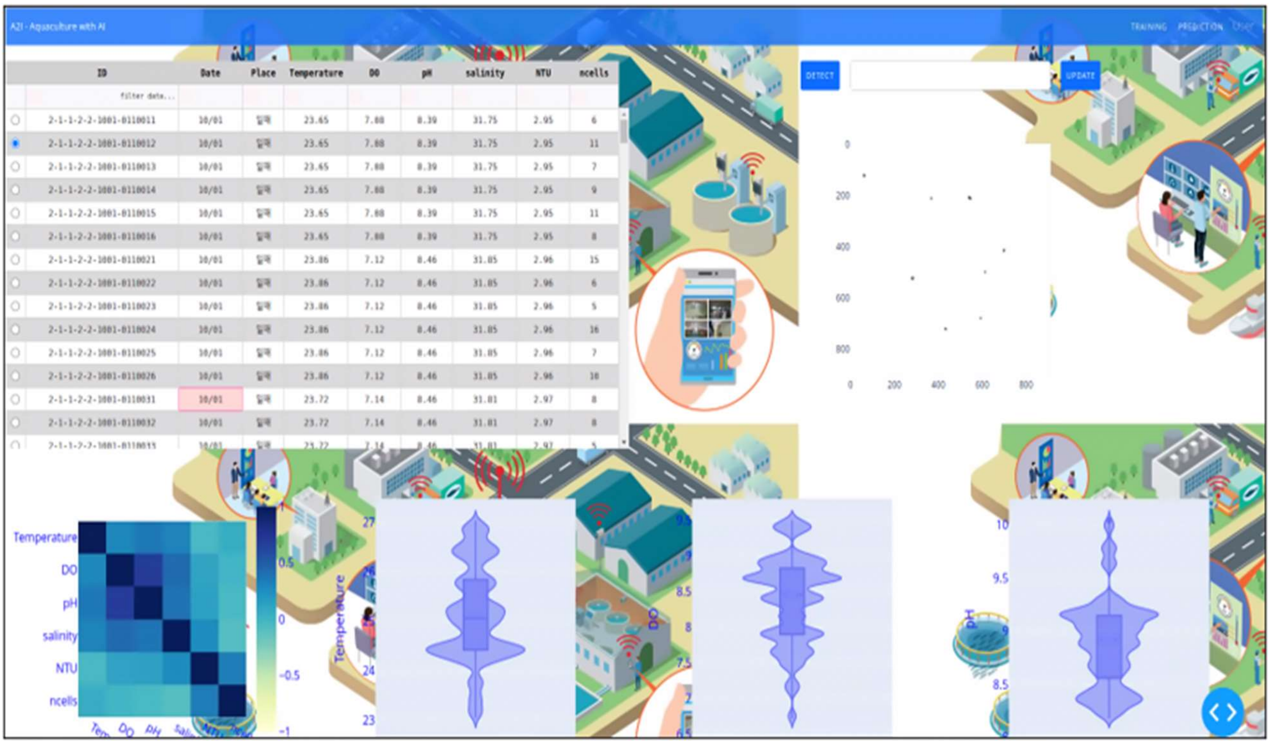


Figure 9. Data Analysis Demo allows us to select the sample. This system visualizes the microscopy image, correlation matrix between every measurement indexes and features values distribution of that sample.

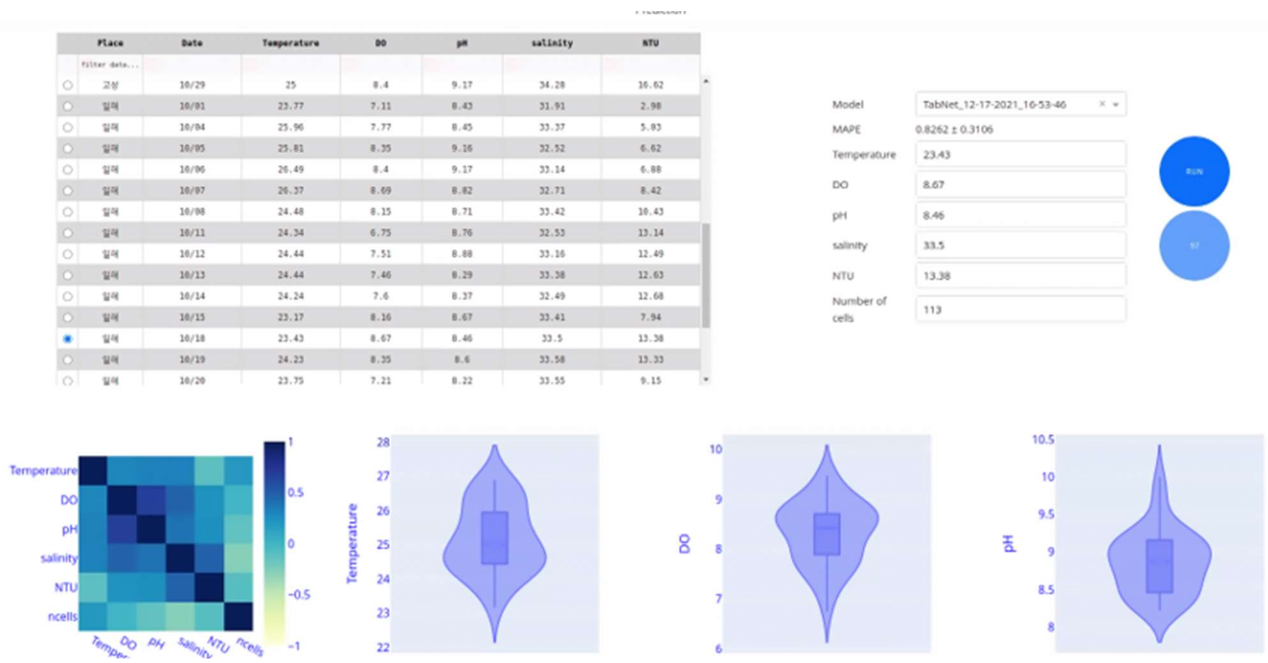


Figure 10. Prediction Demo shows the test results. This stage has option for load the saved models for predicting, evaluation metrics and presents the results of number of cells.

V. CONCLUSION

In this research, we developed a deep learning-based system with a novel deep learning method implemented for aquaculture food organism quality prediction that predicts the cells counting of water from data sensors to control the water quality. The application of the attention tabular learning method shows impressive improvement compared to the whole benchmark traditional machine learning models. However, our system can continue evolving based on temporal context information that leverages interpretive sources from the past to predict future results. Our future study will focus on implementing other deep learning models and developing the system according to the time-series base.

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Authors

Trong-Nghia Nguyen

He received a B.S. degree from the Department of Information Technology, Hue University of Science and Technology, Vietnam, in 2018 and an M.S. degree from the Department of Computer Vision, MICA, Hanoi University of Science and Technology, Vietnam, in 2020. Currently, He is pursuing a Ph.D. degree from the Department of Artificial Intelligence Convergence. He has joined the PR Lab since 04-2021. His research is focused on medical image processing, rapid response systems, and treatment recommendations.

Soo-Hyung Kim

He received his B.S. degree in Computer Engineering from Seoul National University in 1986 and the M.S. and Ph.D. degrees in computer science from the Korea Advanced Institute of Science and Technology, in 1988 and 1993, respectively. Since 1997, he has been a Professor with the School of Electronics and Computer Engineering, Chonnam National University, South Korea. His research interests include pattern recognition, document image processing, medical image processing, and deep learning.

Nhu-Tai Do

He received the B.S. in Information System major from HCM City University of Foreign Language – Information Technology, Vietnam in 2005 and his M.S. in Information System Management from International University, Vietnam National University at HCMC, Viet Nam in 2017. From 2005 to 2017, he was a lecturer in Faculty of Information Technology, HCM University of Foreign Languages and Information Technology, Vietnam. Since 2017, he is Ph.D. candidate in the Department of Computer Science, Chonnam National University, Korea. His research interests are pattern recognition, deep learning, computer vision, and parallel programming.

Thai-Thi Ngoc Hong

She is currently a senior student in the department of Business of Economics and is pursuing a second B.S. degree in Software Engineering, Chonnam National University, South Korea. Her research interest includes data mining, Data Science in Economics and Finance.

Hyung-Jeong Yang

She received the B.S., M.S., and Ph.D. degrees from Chonbuk National University, South Korea. She is currently a Professor with the Department of Artificial Intelligence Convergence, Chonnam National University, Gwangju, South Korea. Her main research interests include multimedia data mining, medical data analysis, social network service data mining, and video data understanding.

Guee-Sang Lee

He received the B.S. degree in electrical engineering and the M.S. degree in computer engineering from Seoul National University, South Korea, in 1980 and 1982, respectively, and the Ph.D. degree in computer science from Pennsylvania State University, in 1991. He is currently a Professor with the Department of Artificial Intelligence Convergence, Chonnam National University, South Korea. His research interests include image processing, computer vision, and video technology.