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Research Paper

A Temporal–Spatial Deep Learning Framework for Intelligent Fish Growth Modelling Using CNN-Driven Ensemble Regression

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ABSTRACT

Aquaculture production has increased over the last decade; however, field observations suggest that nearly 20% of potential yield is lost in each cycle due to inadequate monitoring and imprecise growth estimation. Although overall production continues to rise, the lack of dependable automated prediction systems restricts operational efficiency in fish farming. Conventional practices, which involve manually handling fish to measure length and weight, are time-consuming, inconsistent, and dependent on operator expertise. Moreover, frequent handling disrupts the aquatic environment, induces stress in fish, and negatively influences their growth patterns. These limitations hinder continuous monitoring, particularly in environments with rapidly fluctuating conditions. Practical aquaculture operations, including adaptive feeding strategies, early identification of growth anomalies, and dynamic environmental control, require accurate and real-time predictive capabilities. Existing solutions predominantly rely on Linear Regression (LR), Ridge Regression (RR), and Lasso Regression (Lasso), which are insufficient for modeling complex, non-linear interactions in aquaculture data. To overcome these challenges, this study introduces ConvETR, a hybrid regression framework that integrates a Convolutional Neural Network (CNN) with an Extra Trees Regressor (ETR). The CNN extracts meaningful temporal and spatial features from continuous sensor inputs, capturing behavioral and environmental variations, while the ETR enhances prediction stability by effectively handling noise and non-linearity. This non-intrusive and scalable approach enables accurate real-time predictions, improves decision-making, and supports efficient and sustainable aquaculture management.

Keywords: IoT-based Aquaponics, Real-Time Monitoring, Temporal-Spatial Feature Extraction, Smart Aquaculture Systems.

1. INTRODUCTION

The quality of water directly affects the rate of growth, efficiency of feed, and the overall health rate of the fish, plants, and bacteria. Insufficient knowledge about species selection poses a significant challenge in aquaponics farming, as it heavily relies on the water quality parameters. To address the challenges of conventional models, we have developed an effective IoT-based water quality prediction model, more specifically designed for aquaponic Fish ponds Advanced monitoring techniques are adopted for the prediction of water quality in aquaponics by anticipating the changes in key water parameters. The anticipation of parameters includes concentration of dissolved oxygen, level of PH, level of ammonia, nitrate, and nitrite and temperature. The primary objective of the water quality prediction techniques. Furthermore, it is helpful to rectify the negative impacts on plant health and fish health in the aquaponic system by using these monitoring techniques. When the level of dissolved oxygen drops too low several procedures can be taken for improving the oxygen preventing stress on the fish. The fish feeding regime is adjusted by the practitioners for ensuring that the plants receive the

necessary nutrients for their healthy growth by understanding the nutrient levels in the water and nutrient requirements of the plants.

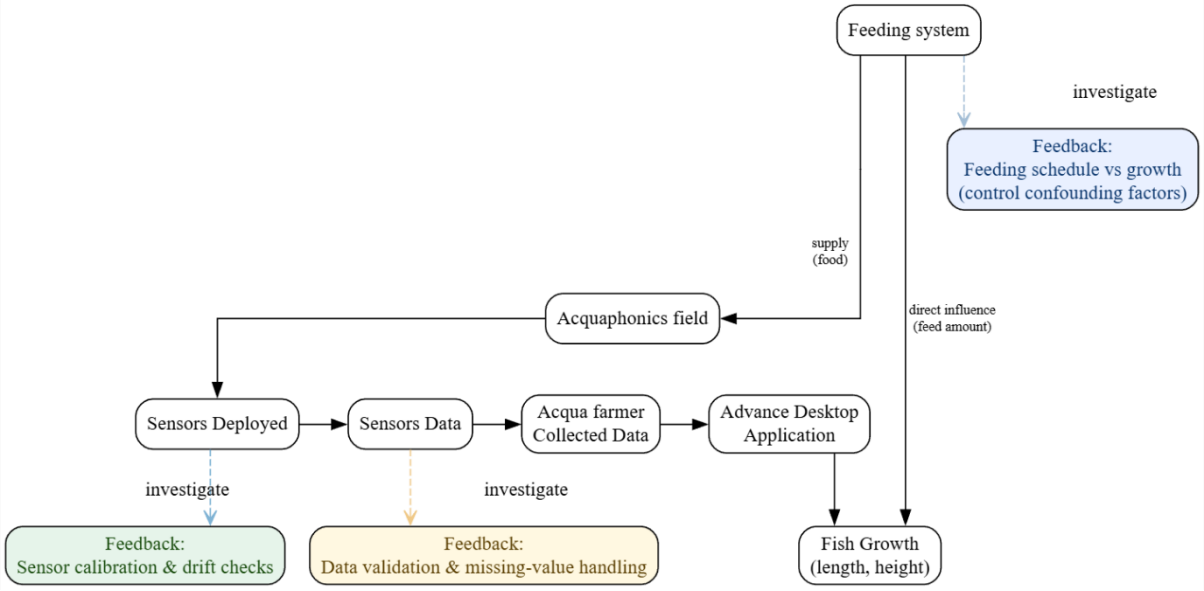


Figure 1. Research motivation of Fish growth analysis

As shown in fig 1 the motivation for monitoring and improving fish growth within an aquaponics environment by integrating feeding systems, field conditions, sensor data, human observation, and desktop analysis. The flow begins in the acquaponics field, where fish are cultivated under controlled water and environmental conditions. Sensors are deployed in this field to continuously measure essential parameters such as temperature, pH, dissolved oxygen, and water quality, all of which directly influence fish health and growth.These sensors transmit real-timesensor data,which forms a critical foundation for understanding environmental fluctuations. Alongside automated sensing, the acqua farmer manually collects complementary data, including visual inspections, feeding observations, and behavioural notes, ensuring that missing or faulty sensor readings can be cross-verified. All collected information then flows into an advanced desktop application, where it is organized, interpreted, and used to monitor fish growth outcomes, represented as measurable traits such as length and height

2. LITERATURE SURVEY

Recent advancements in aquaculture have shifted from manual oversight to data-driven management. Research in this domain primarily focuses on integrating Internet of Things (IoT) sensors with Deep Learning (DL) architectures to enhance productivity and environmental sustainability.

2.1 Data-Driven and Machine Learning-Based Fish Growth Modeling

Chen *et al.* [1] proposed a hybrid framework combining empirical growth modeling with a data-driven approach using Long Short-Term Memory (LSTM) networks. Their method incorporated stochastic data generation using normal distribution and introduced a weighted optimization strategy to improve short-term prediction accuracy. Similarly, Purushottam *et al.* [9] applied multiple regression-based machine learning algorithms, including KNN and Decision Tree Regression, achieving high prediction accuracy (above 99%) for fish harvest weight estimation in aquaponic systems.

Jongwon *et al.* [7] addressed challenges in heterogeneous datasets by integrating mixed data sampling (MIDAS) with overlapping mixtures of Gaussian processes (OMGP). Their probabilistic modeling approach effectively handled environmental and fish weight data, improving prediction reliability under mixed data conditions.

2.2 Environmental and Physiological Factors Influencing Fish Growth

Clark *et al.* [2] investigated the impact of climate warming on fish size reduction through the Gill Oxygen Limitation (GOL) hypothesis, highlighting the mismatch between oxygen supply and

metabolic demand during growth. Mariu *et al.* [14] further emphasized the role of environmental parameters such as temperature, pH, salinity, and dissolved oxygen in influencing fish metabolism, physiology, and survival.

Ragheb *et al.* [11] analyzed fish growth patterns using length-weight relationships and condition factors, providing statistical validation of growth variability across species. Additionally, D'Avignon *et al.* [13] studied the combined effects of microplastics and thermal stress, concluding that temperature plays a more dominant role in influencing growth performance.

2.3 Nutritional, Biological, and Microbiome-Based Growth Enhancement

Jose Gv *et al.* [3] examined the effects of dietary arachidonic acid (ARA) on fish physiology, immune response, and fatty acid composition, demonstrating improvements in intestinal health and immune regulation. Gopalraaj *et al.* [4] explored the role of protease enzymes as feed supplements, highlighting their benefits in enhancing nutrient digestibility, fish growth, and water quality.

Kalita *et al.* [8] reviewed the role of probiotics and gut microbiota in improving fish immunity and growth, emphasizing microbial interactions and metabolic contributions. Goodrich *et al.* [6] discussed interindividual growth variability, linking metabolism, gut morphology, and behavioral traits to growth performance.

2.4 Aquaponics, Biofloc, and Sustainable Aquaculture Systems

Mohamed Iv *et al.* [5] developed an aquaponics system integrating hydroponics and fish culture, demonstrating optimal water quality conditions for enhanced fish and plant growth. Hasanuzzaman *et al.* [12] evaluated biofloc technology (BFT), showing improved growth rates, nutritional composition, and immune responses compared to traditional systems.

Radinger *et al.* [15] conducted large-scale ecosystem-based experiments, concluding that habitat enhancement strategies are more effective than conventional fish stocking methods in improving fish populations, particularly for juvenile growth stages.

2.5 Growth-Survival Dynamics and Ecological Perspectives

Robert *et al.* [10] revisited the Growth-Survival Paradigm (GSP), analyzing extensive datasets and revealing that growth-related survival advantages are not universally consistent. Their findings suggest that ecological and environmental complexities significantly influence survival-growth relationships, challenging traditional assumptions.

3. PROPOSED SYSTEM

The proposed fish growth prediction system, illustrated in Fig. 2, integrates IoT-enabled water quality monitoring with a hybrid CNN–ETR framework to accurately estimate fish length and weight. In contrast to traditional approaches such as linear, ridge, and lasso regression—which rely on assumptions of linear relationships—the proposed model effectively captures complex, non-linear interactions between environmental conditions and biological growth patterns. The system processes sensor data through a CNN-based deep feature extraction mechanism, followed by regression using the Extra Trees Regressor to enhance prediction robustness. Furthermore, the complete model is implemented as a desktop application using Tkinter, allowing users to input real-time parameters and obtain reliable growth predictions.

The dataset comprises time-series aquaculture sensor measurements, including temperature, turbidity, dissolved oxygen, pH, ammonia, nitrate levels, and population-related attributes. These features are associated with target variables such as fish length (cm) and fish weight (g). Initially, the dataset undergoes preprocessing steps, including duplicate removal, missing value imputation, and normalization of numerical features to ensure stable and consistent model training. Subsequently, Exploratory Data Analysis (EDA) is conducted to examine data distributions and uncover correlations between environmental variables and fish growth indicators.

As part of the baseline evaluation, Linear Regression is employed; however, it demonstrates limited performance due to its inability to model non-linear dependencies. Ridge Regression enhances model

stability by mitigating multicollinearity through L2 regularization, while Lasso Regression performs implicit feature selection via L1 regularization. Despite these improvements, both methods remain insufficient in capturing the intricate, non-linear relationships inherent in aquaculture growth dynamics, thereby justifying the need for the proposed hybrid deep learning approach.

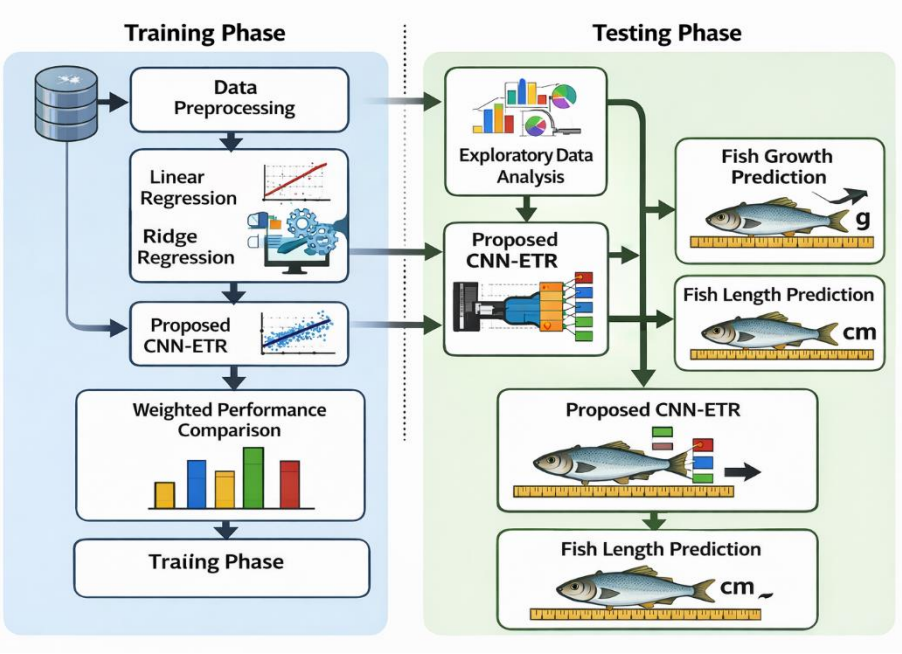


Figure 2. Proposed system architecture of aquaponics

To address these limitations, the proposed ConvETR model integrates a Convolutional Neural Network (CNN) for deep feature extraction with an Extra Trees Regressor (ETR) for ensemble-based prediction. This hybrid approach enables the model to effectively learn complex and non-linear growth patterns from aquaculture data. The performance of the proposed model is evaluated using standard regression metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2 score). Experimental results demonstrate that the ConvETR model outperforms conventional methods in terms of both accuracy and robustness.

Furthermore, the trained model is validated on unseen test data to assess its generalization capability in predicting fish length and weight. The entire framework is deployed as a user-friendly desktop application developed using Tkinter, allowing users to input real-time water quality parameters and obtain accurate fish growth predictions efficiently

4. RESULTS ANALYSIS

The Figure 3. presents a combined visualization of feature relationships and data variability in the aquaponics dataset, where the correlation heatmap on the left illustrates the strength and direction of relationships among environmental and biological parameters, and the box plot on the right highlights the distribution of fish weight along with potential outliers. From the heatmap, fish length and fish weight exhibit a very strong positive correlation (0.91), indicating that increases in fish length are strongly associated with increases in fish weight, while nitrate concentration also shows a strong positive correlation with fish length (0.74) and fish weight (0.53), suggesting is importance in fish growth. Turbidity demonstrates moderate positive correlations with fish length (0.51) and nitrate (0.54), whereas pH shows a moderate negative relationship with fish weight (−0.59), indicating that higher pH levels may adversely affect weight gain. Other parameters such as temperature and ammonia show weak correlations with growth metrics, implying a relatively smaller influence under the observed conditions. The box plot reveals that while most fish weight values are concentrated within a moderate range, several high-value outliers are present, indicating variability in growth and the occurrence of unusually

large fish, which may result from biological diversity or favorable localized conditions within the system.

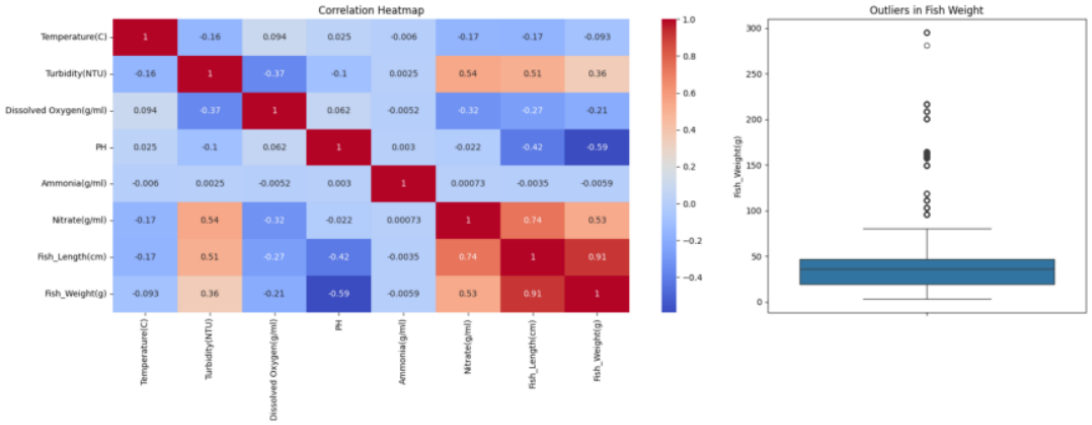


Figure 3. Exploratory analysis of feature relationships and data variability.

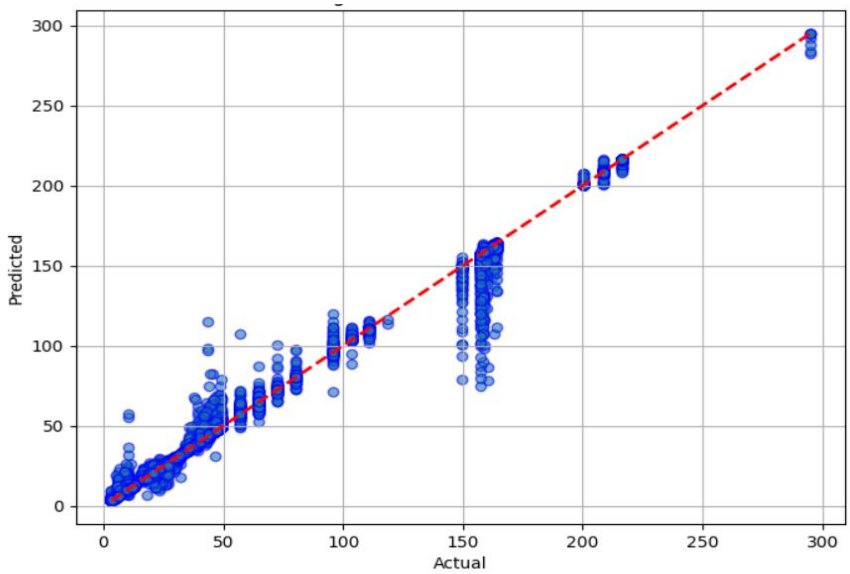


Figure 4. Illustration of scatter plot using proposed ConvETR model

Figure 4 shows the actual vs. predicted fish weight results using the ConvETR model, where blue dots represent individual predictions and the red dashed line indicates the ideal one-to-one prediction line. The points are tightly clustered along the reference line across the entire weight range, demonstrating an excellent agreement between actual and predicted values. Compared to linear, Lasso, and Ridge regression plots, this figure exhibits significantly less dispersion and minimal deviation from the ideal line, indicating very low prediction error and strong generalization capability. Even at higher weight values, the predictions remain highly accurate with only minor variance, highlighting the model's ability to capture complex and nonlinear relationships in the data.

	created_at	entry_id	Temperature(C)	...	Ammonia(g/ml)	Nitrate(g/ml)	Population
	2021-06-19 00:00:04 CET	1941	23.7500	...	5.15546	114	50
	2021-06-19 00:00:26 CET	1942	23.7500	...	4.53072	114	50
	2021-06-19 00:02:03 CET	1945	23.7500	...	5.21473	113	50
	2021-06-20 05:15:03 CET	6754	25.3125	...	4.63497	112	50
	2021-06-20 05:15:22 CET	6755	25.3125	...	5.23464	109	50
	2021-06-20 05:15:42 CET	6756	25.3125	...	4.61742	112	50
	2021-06-20 05:16:01 CET	6757	25.2500	...	4.49651	112	50
	2021-06-23 21:26:07 CET	14703	23.6875	...	20.53721	96	50
	2021-06-23 21:26:27 CET	14704	23.6875	...	19.53849	95	50
	2021-06-23 21:26:46 CET	14705	23.6875	...	25.88264	96	50
0	2021-06-29 23:59:18 CET	23057	23.8750	...	70.18184	91	50
1	2021-06-29 23:59:37 CET	23058	23.8750	...	67.57928	95	50
2	2021-06-29 23:59:57 CET	23059	23.8750	...	48.23458	99	50
3	2021-06-30 00:00:16 CET	23060	23.8750	...	67.89865	97	50

Figure 5. Prediction on sample test data using proposed ConvETR model

Figure 5 illustrates the prediction framework for sustainable aquaponics fish farming using real-time environmental and population data collected at regular intervals. The dataset includes parameters such as water temperature, ammonia concentration, nitrate levels, and fish population, which together influence fish growth prediction. As shown in Figure 5, the water temperature remains relatively stable in the range of 23.75°C to 25.31°C, creating suitable thermal conditions for fish health. Ammonia levels vary from approximately 4.55 g/ml to 20.54 g/ml, while nitrate concentrations show wider fluctuations, increasing from about 96 g/ml to nearly 114 g/ml across different timestamps. The fish population is consistently maintained at 50, indicating controlled stocking density. These continuously logged parameters are fed into the prediction framework to estimate growth-related outcomes, enabling timely monitoring of water quality, early detection of stress conditions, and data-driven decision-making for sustainable aquaponics management.

5. CONCLUSION

The research provides an advanced and intelligent solution for predicting fish growth while ensuring efficient water quality management. The experimental analysis indicates that conventional models such as LR, Lasso, and RR exhibit limited capability in capturing the complex relationships between environmental conditions and fish growth. These approaches rely on simplified assumptions, which restrict their effectiveness when dealing with dynamic and non-linear aquaculture data. In contrast, the ConvETR model demonstrates significantly improved predictive performance by effectively learning intricate patterns from multi-parameter sensor data. The integration of CNN enables deep feature extraction from environmental inputs, while the ETR component enhances prediction reliability through ensemble learning. This combination allows the model to better understand the interaction between water quality parameters and biological growth processes. Furthermore, the system's integration with real-time IoT data supports continuous monitoring and adaptive prediction, making it highly suitable for modern aquaponics environments. The deployment as a Tkinter-based application ensures practical usability, allowing users to input live parameters and obtain instant growth predictions. The proposed framework enhances operational efficiency, reduces dependency on manual monitoring, and supports informed decision-making in aquaculture. By leveraging intelligent data-driven modeling, the system contributes to sustainable fish farming practices and improved resource management in aquaponics systems.

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