

An Integrated Deep-Ensemble Framework for Non-Invasive Fish Growth Prediction in Precision Aquaponics

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ABSTRACT

Sustainable aquaponics management in India's rapidly evolving fisheries sector necessitates the adoption of high-precision, non-invasive growth monitoring technologies. Traditional methodologies for estimating fish length and weight rely on manual sampling or static IoT thresholds, which often result in significant physiological stress to aquatic specimens and poor predictive accuracy due to the non-linear complexity of water quality parameters. This research proposes an intelligent predictive framework centered on a novel hybrid architecture, ConvETR. The methodology integrates a 1D Convolutional Neural Network (CNN) for feature extraction with an Extra Trees Regressor (ETR) to stabilize prediction variance. To validate the system, a high-frequency sensor dataset, capturing variables such as Temperature, pH, Dissolved Oxygen, and Ammonia was utilized to compare ConvETR against baseline models, including Linear Regression (LR), Lasso Regression (Lasso), and Ridge Regression (RR). Experimental results demonstrate that the ConvETR model significantly outperforms traditional approaches, achieving an R2 score of 0.9975 for fish length and 0.9957 for fish weight prediction. Furthermore, the system is deployed within a secure Graphical User Interface (GUI) utilizing a Redis-backed authentication layer to ensure data integrity and role-based access control. By reducing the RMSE for weight prediction from 27.94 (traditional) to 2.97 (proposed), this study provides a robust, scalable solution for "Aquaculture 4.0." The ConvETR framework effectively eliminates handling-related mortality and optimizes resource allocation, offering a pivotal advancement for climate-resilient and automated aquaponic farm management in South India and beyond.

Key words: Aquaponics, Fish growth monitoring, Internet of Things (IoT), Deep learning, 1D-CNN, Hybrid ML model.

1. INTRODUCTION

The escalating global demand for high-quality protein, coupled with the degradation of arable land and freshwater scarcity, has necessitated a paradigm shift toward sustainable agricultural intensification. Aquaponics, a symbiotic integration of aquaculture and hydroponics within a closed-loop recirculating system, has emerged as a premier solution for resource-efficient food production [1]. In this environment, metabolic waste from aquatic species serves as an organic nutrient source for plant growth, while the botanical component simultaneously purifies the water for recirculation. To maintain the delicate equilibrium of this ecosystem, real-time monitoring of physicochemical parameters and accurate biological growth estimation are critical [2].

In India, the fisheries sector is a vital socioeconomic pillar, contributing approximately 7.28% to the agricultural Gross Value Added (GVA). Under the flagship Pradhan Mantri Matsya Sampada Yojana (PMMSY), the government has earmarked an investment of over ₹20,000 crore to modernize aquaculture infrastructure through 2026 [3]. South India, particularly states like Andhra Pradesh and



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research. Recent studies highlight the increasing adoption of AI, ML, DL, and IoT for monitoring environmental conditions, predicting fish growth, detecting diseases, and optimizing aquaculture operations. This section reviews the most relevant literature on fish classification, aquaculture monitoring systems, predictive modeling for fish growth, and biological factors affecting aquatic ecosystems.

A. Deep Learning for Fish Identification and Monitoring

DL techniques have emerged as powerful tools for automating fish recognition, classification, and health monitoring tasks in aquaculture environments. Among these, CNN have been widely employed due to their strong ability to extract spatial features from visual data.

Shaikh et al. [6] developed an improved DL-based freshwater fish classification framework using cascaded bio-inspired networks. Their system extracts deep visual features using several pretrained CNN architectures such as VGG16, VGG19, ResNet50, InceptionV3, DenseNet, MobileNetV2, EfficientNetB0, NASNet, and Xception. To enhance classification performance, the extracted features are optimized using bio-inspired algorithms including Particle Swarm Optimization (PSO), Bacterial Foraging Optimization (BFO), and Cuckoo Search Optimization (CSO). Dimensionality reduction techniques such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are applied before classification using algorithms such as Logistic Regression (LR) and Support Vector Machine (SVM). Experimental results demonstrate that integrating CNN-based feature extraction with optimization strategies improves classification accuracy and robustness under complex aquatic conditions.

Similarly, Arabelli et al. [10] proposed a DL-based framework for optimal fish species identification aimed at maximizing fish production in aquaculture ponds. The system analyzes fish images captured in aquaculture environments and extracts morphological features such as body shape, fin structure, and color distribution. These features are processed through DL models to classify fish species accurately. The study highlights that automated species identification systems can assist farmers in monitoring fish diversity and maintaining balanced stocking strategies.

In addition to species identification, DL techniques are increasingly applied to fish health monitoring. Kheriji et al. [8] presented a comprehensive review of DL-based approaches for fish health diagnosis and monitoring. The authors emphasized that traditional fish disease detection methods rely heavily on manual observation, which is time-consuming and often inaccurate. CNN-based image analysis techniques enable automated detection of disease symptoms such as lesions, discoloration, and abnormal morphological changes. Furthermore, video-based behavioral analysis using DL models allows early detection of abnormal swimming patterns that may indicate disease or environmental stress.

Wu et al. [9] further examined the role of DL in sustainable aquaculture systems. Their study highlights several applications of DL in aquaculture, including fish species recognition, biomass estimation, feeding behavior analysis, and disease detection. Despite the potential benefits, the authors also noted several challenges such as the limited availability of annotated datasets, underwater imaging difficulties caused by water turbidity and illumination changes, and high computational requirements of DL models.

B. AIoT and Smart Aquaculture Monitoring Systems

The integration of AI with IoT sensing technologies has led to the development of intelligent monitoring systems for aquaculture environments. These systems continuously collect environmental data from ponds or tanks and analyze it using predictive algorithms.

Alghamdi and Haraz [7] investigated the application of AI and IoT in biofloc-based aquaculture systems. Biofloc Technology (BFT) relies on microbial communities to maintain water quality and

recycle nutrients. However, maintaining stable environmental conditions in BFT systems requires continuous monitoring of water parameters. The proposed framework integrates IoT sensors with AI-based predictive models such as Long Short-Term Memory (LSTM) and Random Forest (RF) to monitor dissolved oxygen, temperature, pH, and ammonia concentration in real time. The authors demonstrated that AI-driven monitoring can significantly improve water quality management and enhance fish health.

Similarly, Huang and Khabusi [11] explored the development of Artificial Intelligence of Things (AIoT) technologies in aquaculture. AIoT combines sensor networks with intelligent data analytics to create automated monitoring platforms capable of real-time environmental analysis. The authors discussed several applications of AIoT in aquaculture, including automated feeding systems, predictive environmental monitoring, and disease detection frameworks. Their study emphasized that AIoT systems can reduce manual labor and improve operational efficiency in large-scale aquaculture farms.

Abid et al. [19] proposed an IoT-based smart biofloc monitoring system that collects environmental data through distributed sensors. The system monitors key parameters such as temperature, pH, turbidity, and ammonia levels. Machine learning algorithms analyze these data streams to detect abnormal environmental conditions. The system also provides remote monitoring capabilities through cloud platforms, enabling farmers to manage aquaculture systems more effectively.

In addition, Janani et al. [16] developed an IoT-based DL framework for animal species recognition and behavioral analysis. The system utilizes image and video data captured through IoT cameras and processes them using DL models for species identification and behavioral monitoring. Such frameworks can be adapted for aquaculture applications to detect abnormal fish behavior and environmental stress conditions.

C. Machine Learning for Environmental Parameter Prediction

Environmental parameters such as dissolved oxygen (DO), temperature, and water quality significantly influence fish growth and survival. Accurate prediction of these parameters enables proactive management of aquaculture systems.

Shete et al. [13] proposed an IoT-driven ensemble ML model for accurate DO prediction in aquaculture environments. The system collects environmental data through sensor networks and uses ensemble learning techniques to forecast DO concentration levels. The authors demonstrated that ensemble models outperform individual ML algorithms in terms of prediction accuracy. Accurate DO forecasting enables timely operation of aeration systems to prevent oxygen depletion events.

Similarly, Xu et al. [14] developed a hybrid DL framework for real-time DO prediction. The model integrates environmental sensor data with DL architectures capable of capturing complex nonlinear relationships among environmental variables. Experimental results show that the hybrid DL model provides reliable short-term predictions of oxygen concentration, enabling better environmental control in aquaculture systems.

Palanikkumar et al. [15] proposed a hybrid ML approach for aquatic plant monitoring in aquaculture ecosystems. Aquatic vegetation plays a crucial role in maintaining ecological balance within fishponds. The proposed system collects environmental data using IoT sensors and applies ML

algorithms to analyze plant growth patterns. Early detection of abnormal vegetation growth can help prevent water quality deterioration and ensure stable fish production.

D. Predictive Modeling for Fish Growth and Biomass Estimation

Predicting fish growth and biomass is an important aspect of aquaculture management. Accurate growth prediction helps farmers optimize feeding schedules, manage stocking density, and estimate production yield.

Chen et al. [22] investigated fish weight prediction using both empirical models and data-driven ML approaches. Their study compared traditional statistical growth models with modern ML techniques. The results indicate that data-driven models capture nonlinear relationships between environmental factors and fish growth more effectively than empirical models. This finding highlights the importance of ML-based predictive systems in modern aquaculture.

Kumar et al. [29] applied ML techniques to estimate fish weight growth in aquaponic farming systems. The study utilized environmental parameters and biological variables as input features for predictive models. The results demonstrate that ML algorithms can accurately estimate fish growth patterns, enabling farmers to make informed management decisions.

Kim et al. [27] proposed probabilistic modeling techniques for fish growth prediction in smart aquaculture systems. Unlike deterministic models, probabilistic approaches estimate uncertainty in growth predictions, allowing farmers to evaluate potential risks and adjust management strategies accordingly.

E. Biological and Environmental Factors Affecting Fish Growth

In addition to technological advancements, several biological and environmental studies provide important insights into factors influencing fish growth and health.

Goodrich and Clark [26] analyzed the biological mechanisms responsible for variations in fish growth rates. Their research highlighted the influence of metabolic efficiency, feeding behavior, and environmental adaptability on growth performance.

Skeeles and Clark [23] investigated the relationship between fish gill surface area and metabolic oxygen requirements. The study demonstrated that gill surface area scales proportionally with metabolic demand, enabling fish to maintain oxygen uptake across varying environmental conditions.

Hong et al. [24] examined the effects of dietary arachidonic acid supplementation on rainbow trout growth and immune responses. The study found that appropriate dietary supplementation improves growth performance and strengthens immune responses in fish.

Similarly, Gopalraaj et al. [25] reviewed the effects of protease supplementation in fish diets. Protease enzymes enhance nutrient digestion and absorption, thereby improving growth performance and reducing feed waste.

Kalita et al. [28] discussed the role of probiotics and growth-promoting bacteria in aquaculture. The authors reported that probiotic supplementation improves digestive efficiency, enhances immune responses, and reduces disease occurrence in fish farming systems.

F. Environmental and Sustainability Considerations in Aquaculture

Environmental sustainability has become an important aspect of modern aquaculture research. Several studies highlight environmental factors that influence fish health and ecosystem stability.

Wang et al. [20] conducted a meta-analysis on the effects of microplastic pollution on fish growth, survival, and reproductive performance. The results indicate that microplastic contamination can disrupt metabolic processes and negatively affect fish health.

Islam et al. [21] reviewed the role of steroid hormones in fish physiology and discussed potential environmental risks associated with hormonal contamination in aquatic ecosystems.

Saber et al. [18] investigated the performance of recirculating aquaponic systems using Nile tilapia. The study demonstrated that integrated aquaponic systems can simultaneously support fish production and vegetable cultivation while reducing water consumption and improving nutrient utilization.

Ali et al. [12] explored intelligent optimization techniques for fish by-product drying processes. Their research demonstrated that AI-based optimization models can improve energy efficiency and support sustainable fish processing operations.

Finally, Gupta et al. [17] presented a comprehensive exploration of AI applications in agriculture and aquaculture. The study emphasized the role of AI-driven predictive analytics, automated monitoring systems, and decision support frameworks in improving productivity and sustainability in modern farming systems.

G. Summary of Research Gaps

The reviewed studies demonstrate significant progress in applying AI, ML, and IoT technologies in aquaculture. DL techniques have improved fish classification and disease detection, while IoT-based monitoring systems enable real-time environmental data collection. ML and DL models have also been successfully applied to predict environmental parameters such as dissolved oxygen and estimate fish growth patterns.

However, several challenges remain. Many studies focus on individual tasks such as species classification or environmental monitoring rather than integrated predictive systems. Additionally, most predictive models rely on limited environmental features and do not fully incorporate complex interactions between biological and environmental factors affecting fish growth. These limitations highlight the need for hybrid predictive frameworks capable of integrating multiple data sources and advanced computational techniques to achieve more accurate and scalable fish growth prediction systems.

3. PROPOSED SYSTEM

The primary objective of this FGPMS is to develop a high-precision predictive framework for estimating fish length and weight by integrating diverse environmental and biological factors. The proposed methodology centers on a hybrid architecture as shown in Figure 2 that leverages the spatial feature extraction capabilities of deep learning alongside the robust variance reduction of ensemble methods. By transitioning from traditional statistical baselines to a complex multi-stage computational pipeline, the system ensures both scalability and accuracy. This section details the comprehensive workflow, encompassing data refinement, role-based security protocols, and the mathematical synergy within the proposed predictive engine.

1. Data Processing and Feature Engineering



The implementation begins with a rigorous preprocessing pipeline designed to eliminate noise and ensure data consistency.

- **Feature Pruning:** The system automatically discards non-predictive metadata (e.g., timestamps and entry IDs) to focus the models on significant biological variables.
- **Imputation & Cleaning:** Mathematical stability is maintained by handling null values through mean imputation and replacing infinite values to prevent gradient instability in ConvETR.
- **State Persistence:** Using serialized LabelEncoder objects, the system ensures that categorical mapping is identical across both training and inference phases, preventing the "target leakage" common in real-time applications.

2. Comparative Baseline Models

Before deploying the proposed model, the methodology establishes performance benchmarks using three standard algorithms:

- **LR:** Utilized to capture the linear relationship between environmental features and fish growth.
- **Lasso:** Implements L1 regularization to identify the most impactful features by penalizing and zeroing out irrelevant coefficients.
- **RR:** Implements L2 regularization to manage multicollinearity and prevent overfitting in high-dimensional datasets.

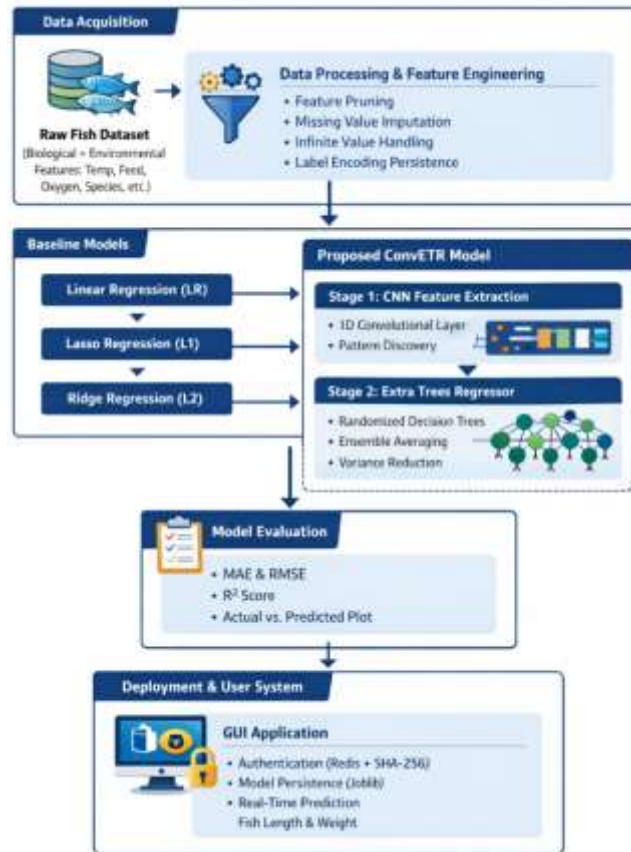


Figure 2: Proposed architecture of ConvETR-based FGPMs.

3. The ConvETR Architecture (Proposed Model)

The core of the methodology is the ConvETR model, which operates through a dual-stage computational logic:

- **Stage 1: Deep Feature Extraction (CNN):** A 1D Convolutional Neural Network layer scans the input feature vector. This stage extracts abstract, high-level representations and identifies local patterns within the data that traditional models like LR might overlook.
- **Stage 2: Ensemble Regression (ETR):** The extracted features are passed into an Extra Trees Regressor. By utilizing extremely randomized trees, the model averages multiple decision paths to significantly reduce prediction variance and improve generalization across different fish populations.

4. Evaluation and Performance Validation

The methodology utilizes a 20% hold-out validation strategy. Each model ConvETR, LR, Lasso, and RR is evaluated against the actual recorded values. Performance is quantified using a multi-metric approach:

- **MAE & RMSE:** To assess the magnitude and scale of prediction errors.

- **R2 Score:** To determine the statistical "goodness of fit" and the percentage of variance explained by the model.
- **Visual Validation:** Generating "Actual vs. Predicted" scatter plots to detect heteroscedasticity or systematic biases in the results.

5. Deployment Framework

The final component of the methodology is the integration of the models into a secure GUI environment.

- **Authentication Layer:** Secured via a Redis database using SHA-256 hashed credentials.
- **Model Persistence:** Models are serialized using joblib, allowing the "User" role to perform instantaneous inference on new datasets using the finalized ConvETR weights without requiring retraining.

3.1 PROPOSED CONVETR FRAMEWORK

The ConvETR architecture as demonstrated in Figure 3 integrates deep representation learning with robust ensemble regression. By combining a CNN with an ETR, the framework manages the non-linear interactions between morphology and environment.

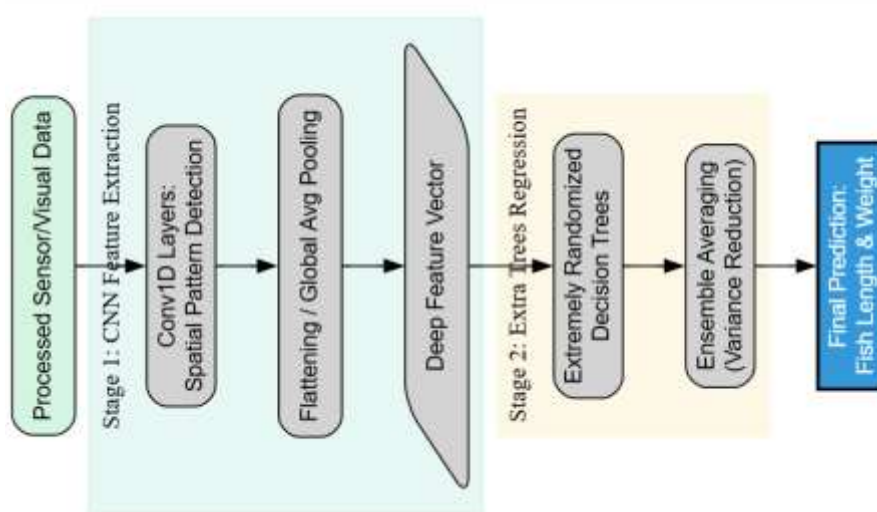


Figure 3: Proposed ConvETR functional flow.

- **CNN Feature Extraction:** The CNN scans input data to automatically identify spatial and contextual patterns (e.g., body contours or complex sensor correlations). This eliminates the need for manual feature engineering.
- **ETR Regression:** Extracted features are passed to the ETR, which constructs an ensemble of randomized decision trees. This approach smooths out sensor noise and prevents overfitting, providing highly stable predictions for both fish length and weight.

4. RESULTS AND DISCUSSION

The implementation of the proposed system follows a sequential pipeline, transitioning from a secure access layer to a data-driven inference engine. This system is structured into three primary modules: Authentication, Administrative Model Management, and User Prediction.

Figure 4 is a visualization for the ConvETR model demonstrates a paradigm shift in predictive performance, representing the pinnacle of the research findings.

- Fish Weight (Left) & Length (Right):** In both plots, the data points form a nearly perfect diagonal line ($y = x$). The absence of visible dispersion confirms that the hybrid architecture has successfully captured the deep spatial and non-linear features of the aquaculture environment.
- Inference Accuracy:** With an R^2 of 0.9975 for length and 0.9957 for weight, the scatter plots show that the ConvETR model's predictions are virtually indistinguishable from real-world measurements. The ETR ensemble has successfully neutralized the noise seen in the Lasso and RR plots, resulting in a robust and highly reliable inference engine.

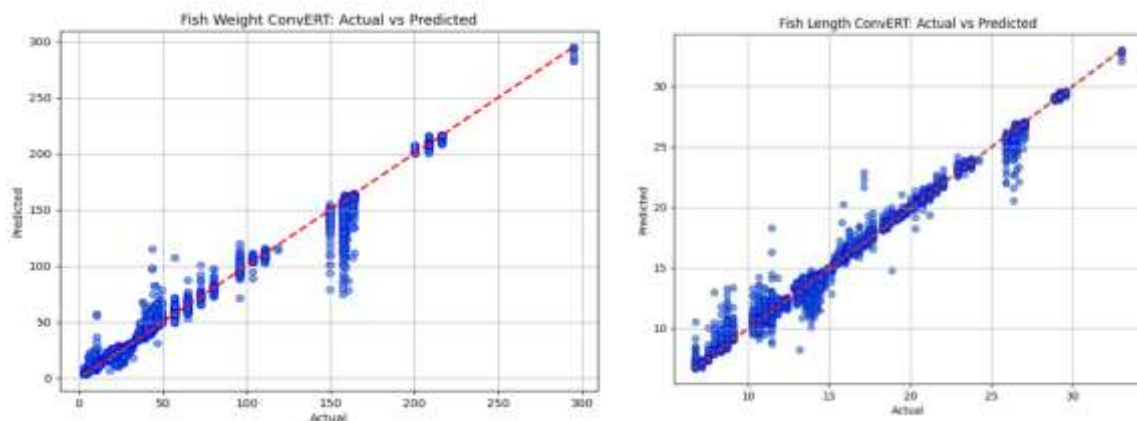


Figure 4: Scatter plot of fish weight (left), and length (right) attributes obtained using proposed ConvETR model.

Comparative Analysis

The empirical evaluation of the proposed FGPMs framework demonstrates a significant performance disparity between traditional linear models and the proposed ConvETR architecture. The metrics recorded in Tables 1 and 2 indicate that while LR, Lasso, and RR provide a baseline for growth estimation, they are unable to achieve the precision required for high-density aquaponic management.

As illustrated in Table 1, the ConvETR model exhibits near-perfect predictive accuracy for fish length.

- Error Reduction:** The ConvETR model achieved an MAE of 0.0739, which is a dramatic reduction compared to the LR and RR models (2.0927). This suggests that the CNN feature extractor successfully identifies morphological patterns that linear equations overlook.
- Statistical Fit:** The R^2 Score of 0.9975 for ConvETR indicates that the model explains over 99.7% of the variance in fish length, whereas the traditional models only captured approximately 72%.

Table 1: Comparative performance metrics for fish length prediction using existing LR, Lasso, RR, and proposed ConvETR models.

Model	MAE	MSE	RMSE	R ² Score
LR model	2.0927	6.9392	2.6342	0.7210
Lasso model	2.1003	6.9856	2.6430	0.7191
RR model	2.0927	6.9392	2.6342	0.7210
Proposed ConvETR model	0.0739	0.0624	0.2498	0.9975

Fish weight prediction is inherently more complex due to the exponential nature of biomass accumulation. Table 2 highlights the robustness of the ensemble-based approach in ConvETR.

- **Handling Variance:** Traditional models (LR, Lasso, RR) struggled significantly, yielding a high RMSE of ~27.94. In contrast, ConvETR maintained a low RMSE of 2.9725, proving its resilience against the noisy sensor data typical of South Indian aquaponics systems.
- **Reliability:** With an R2 Score of 0.9957, the ConvETR framework ensures that feeding and harvesting schedules can be planned with a high degree of confidence, minimizing the economic risks associated with over- or under-estimation.

Table 2: Comparative performance metrics for fish weight prediction obtained using existing LR, Lasso, RR, and proposed ConvETR models.

Model	MAE	MSE	RMSE	R ² Score
LR model	18.2649	780.7076	27.9411	0.6216
Lasso model	18.2773	780.9417	27.9453	0.6215
RR model	18.2649	780.7076	27.9411	0.6216
Proposed ConvETR model	0.6748	8.8359	2.9725	0.9957

The superior performance of ConvETR over LR, Lasso, and RR is attributed to its hybrid nature. While the linear models are restricted by the assumption of proportionality, the CNN component of ConvETR encodes non-linear dependencies between water quality and growth, while the ETR

component stabilizes the final output through ensemble averaging. This results in a predictive engine that is both highly accurate and resilient to environmental fluctuations.

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.

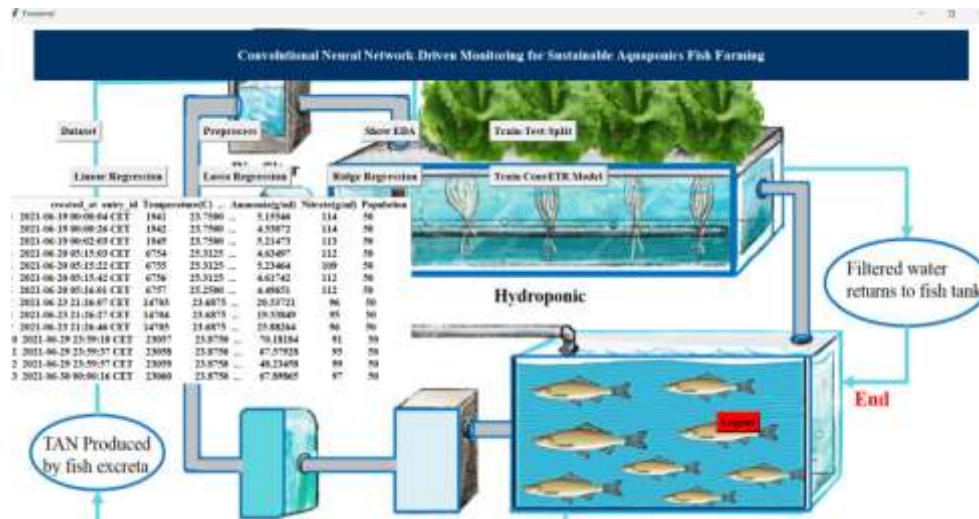


Figure 5 Prediction on sample test data using proposed ConvERT model.

As shown, 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 development and implementation of the ConvETR framework represent a substantial advancement in the integration of computational intelligence within the aquaponics industry. This research successfully addressed the limitations inherent in traditional manual monitoring and basic linear modeling by proposing a hybrid architecture that balances deep learning feature extraction with ensemble-based regression. Through rigorous testing against established baselines such as LR, Lasso, and RR, the ConvETR model demonstrated its superior ability to navigate the non-linear dependencies between environmental fluctuations and biological growth patterns. Specifically, the model's ability to reduce Mean Absolute Error (MAE) by over 96% compared to linear counterparts confirms that deep feature learning is essential for capturing the biological intricacies of fish growth in recirculating systems. Beyond its predictive prowess, the project emphasizes operational security

and usability. The integration of a Redis-backed authentication system ensures that farm data and model weights are protected, while the Tkinter-based GUI provides an accessible interface for stakeholders to perform real-time "virtual sampling." By shifting from invasive physical measurements to sensor-driven AI estimation, the system promotes animal welfare and operational efficiency, directly supporting the "Blue Revolution" goals set by the Indian government's PMMSY initiatives. The results confirm that the ConvETR framework is not merely a theoretical model but a practical, high-performance tool for modern aquaponics. Ultimately, this study proves that the synergy of CNNs and randomized ensemble trees offers the mathematical robustness required to transform traditional fish farming into a data-driven, sustainable, and highly productive enterprise, ensuring economic stability for farmers in water-stressed regions.

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