AN AI-DRIVEN VISION-BASED SYSTEM FOR DISSOLVED OXYGEN PREDICTION AND BEHAVIORAL-AWARE MONITORING IN SMART AQUACULTURE

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Abstract

Maintaining dissolved oxygen (DO) levels at 7–9 mg/L is critical for the physiology of olive flounder (*Paralichthys olivaceus*) in recirculating aquaculture systems (RAS). Conventional water quality sensors are prone to biofouling, require frequent recalibration, and incur substantial operational costs. This study presents a novel, non-invasive, vision-driven artificial intelligence system for continuous DO prediction using overhead tank videos. A 14-day experiment conducted at a commercial RAS facility generated 172,367 synchronized video-–sensor records. The proposed system integrates three stages: (1) YOLOv8s and ByteTrack for automated fish detection and tracking, enabling extraction of behavioral descriptors including locomotor activity, surfacing ratio, swimming velocity, acceleration, and path tortuosity; (2) sensor fusion, combining vision-derived metrics with real-time temperature and pH data through multi-scale feature engineering; and (3) a physics-informed machine learning long short-term memory (PIML-LSTM) incorporating the Streeter–Phelps oxygen transfer equation as a soft ordinary differential equation (ODE) constraint. The proposed model achieved high predictive accuracy (R^2 = 0.9762, *RMSE* = 0.0161 mg/L, *MAPE* = 0.15%, ρ = 0.98), outperforming baseline models by approximately fivefold in prediction error. Behavioral indicators preceding DO decline were detected 57 minutes earlier, enabling proactive aeration control and early-warning monitoring. These results demonstrate the potential of AI-driven, vision-based monitoring as an alternative to conventional electrochemical sensors for precision aquaculture management. the potential of AI-driven, vision-based monitoring as an alternative to conventional 32 electrochemical sensors for precision aquaculture management.

Introduction

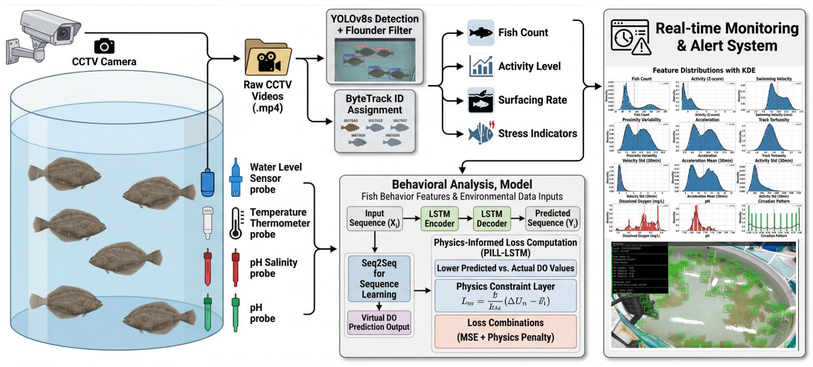
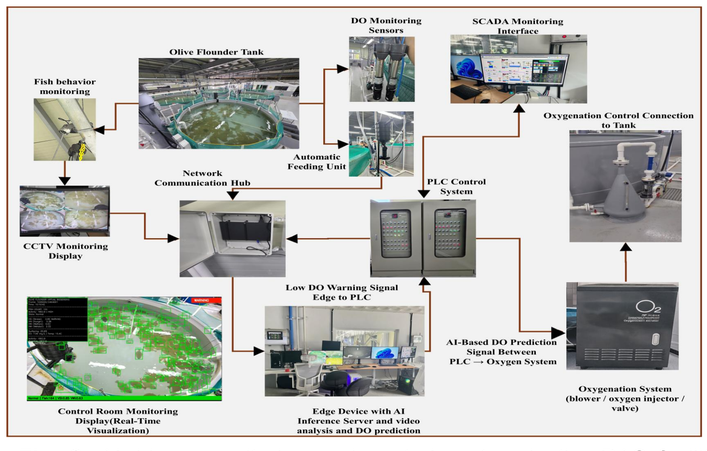


Fig. 1. AI-driven monitoring and control system in the RAS facility.

- Aquaculture now supplies over 50% of global fish demand and continues to expand rapidly, making water quality management essential for sustainable production. Dissolved oxygen (DO) is one of the most critical parameters, directly affecting fish survival, growth, metabolism, and immune function. In species such as olive flounder, optimal DO levels range between 7–9 mg/L, while concentrations below 5 mg/L can cause stress, reduced feeding, and even mortality. However, existing DO monitoring systems rely on costly sensors that require frequent maintenance and are prone to biofouling, limiting their effectiveness in real-world aquaculture environments. In addition, these sensors provide only localized measurements and fail to capture spatial variability within tanks.

- Recent advances in computer vision and deep learning offer a non-invasive alternative by analyzing fish behavior to infer environmental conditions. Models such as CNNs and LSTMs are capable of capturing complex spatial and temporal patterns in behavioral data. Nevertheless, most existing approaches still depend on sensor inputs for accurate DO prediction. To address this limitation, this study proposes a vision-based framework that predicts DO levels using fish behavioral features alone. A physics-informed LSTM model is developed by incorporating the Streeter–Phelps equation as a constraint to ensure physically realistic predictions. The proposed system enables early detection of hypoxia, up to 57 minutes before measurable DO decline, providing a scalable and cost-effective solution for precision aquaculture monitoring.

Material and Methods



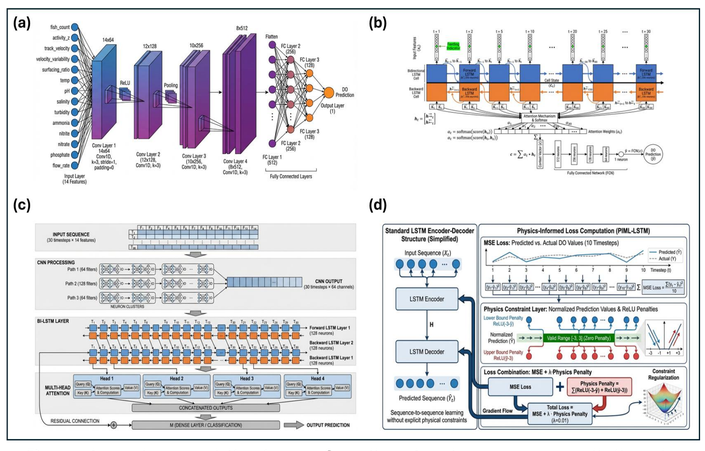


Fig. 2. AI-driven monitoring and control system in the RAS facility, Deep learning architectures for dissolved oxygen prediction in recirculating aquaculture systems.

- This study was conducted in a smart indoor RAS for olive flounder over 14 days under commercial conditions. The system integrated PLC-based sensors, automated feeding, and overhead cameras for synchronized monitoring. Water quality data (DO, temperature, pH, salinity) and video recordings were collected continuously. Fish were detected and tracked using YOLOv8 and ByteTrack, and key behavioral features such as surfacing, activity, and movement patterns were extracted.

- The dataset was processed into time-series sequences and split chronologically for training and testing. Four deep learning models (CNN, BiLSTM, CNN-LSTM, and PIML-LSTM) were developed to predict DO from behavioral data. The PIML-LSTM model incorporated physical constraints using the Streeter–Phelps equation. Models were trained with AdamW and evaluated using standard regression metrics. The framework enables accurate DO prediction without relying on real-time chemical sensors.

Results

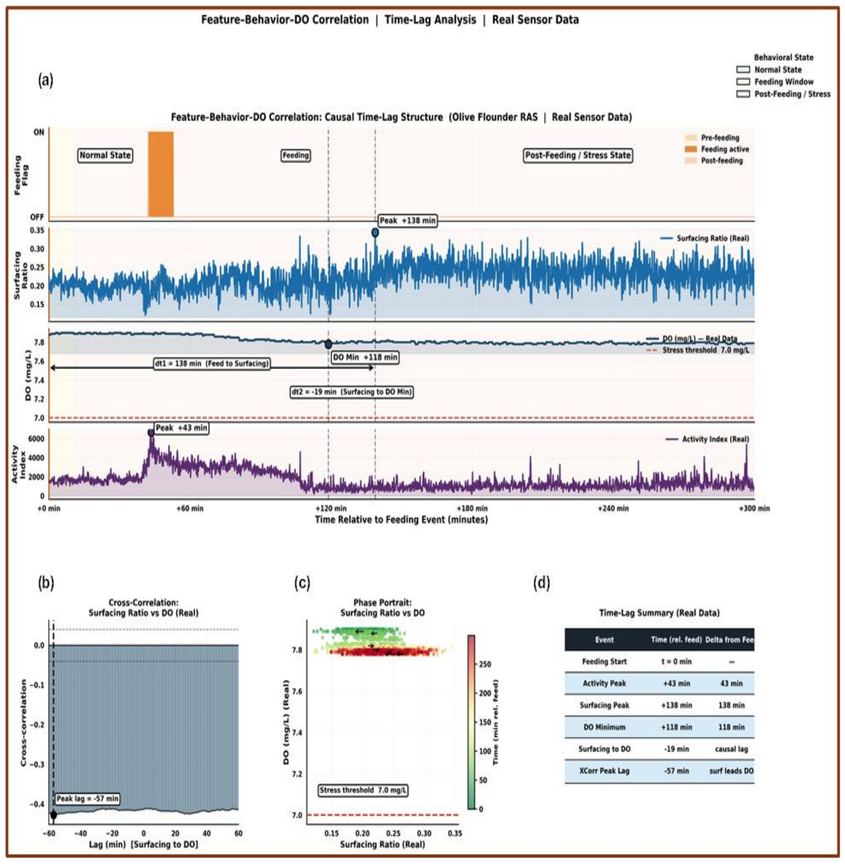


Fig. 3. Feature–behavior–-DO correlation and time-lag analysis in olive flounder RAS: (a) feature-–behavior-–DO correlation showing causal time-lag structure, (b) surfacing ratio, (c) DO (mg·L−1), (d) activity index, (e) cross-correlation between surfacing ratio and DO, (f) phase portrait of surfacing ratio vs. DO, (g) time-lag summary table.

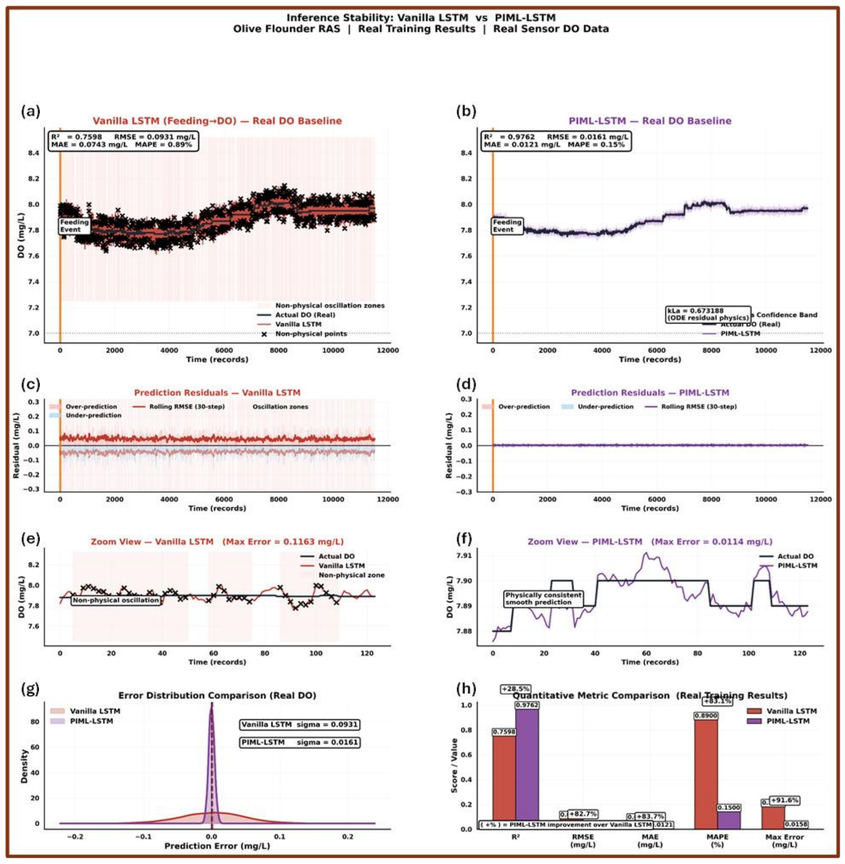


Fig. 4. Comparison of vanilla LSTM and PIML–LSTM for DO prediction in olive flounder RAS: (a) vanilla LSTM prediction, (b) PIML–LSTM prediction, (c–d) residual errors, (e–f) zoomed error views, and (g–h) error distribution and performance metrics.

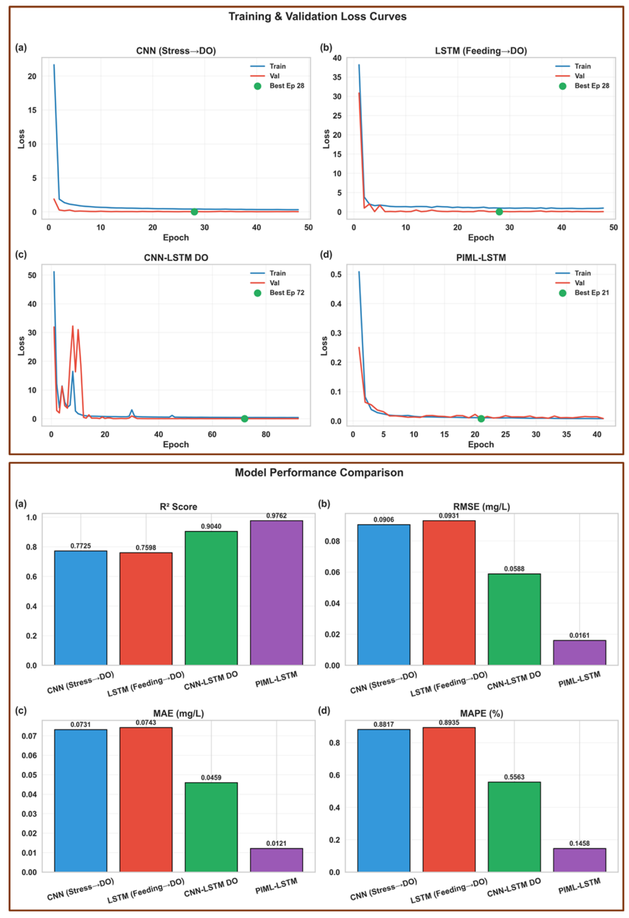


Fig. 5. Training loss curves and performance comparison of deep learning models for DO prediction.