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Artificial Vision in Aquaculture 4.0: Detection and Kinematic Tracking of Biomass Using Single-Stage Neural Networks

Visión artificial en Acuicultura 4.0: Detección y seguimiento cinemático de biomasa mediante redes neuronales de una sola etapa

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Abstract: Computer vision and intelligent systems represent a key trend for automating behavioral monitoring in intensive aquaculture. However, current commercial approaches tend to be costly, inflexible, and dependent on manual human observation. The objective of this study was to develop, train, and validate the system known as EBISU, a non-invasive software framework for evaluating kinematic variables in real time. Methodology: This research is of an applied technological nature; an experimental sample of tilapia (Oreochromis niloticus) was used in a controlled recirculating aquaculture system. The instruments and techniques employed included digital cameras connected to IoT nodes, parallel video processing using PyQt5, and the YOLO deep learning architecture for frame-by-frame geometric detection and tracking. Results: The results demonstrated that the system processes video streams smoothly, accurately determining whether swimming speeds indicate normal parameters or metabolic stress. Discussion: It is noteworthy that EBISU outperforms classical background subtraction by effectively mitigating light reflections and water turbulence. Conclusion: The system successfully automates continuous biolog l monitoring, reducing human error and laying the methodological groundwork for future work in real-time precision aquaculture.

Keywords: Deep learning, YOLO v8, animal welfare, non-invasive monitoring.

Resumen: La visión artificial y los sistemas inteligentes representan una tendencia clave para automatizar el monitoreo conductual en la acuicultura intensiva. Sin embargo, los enfoques comerciales actuales suelen ser costosos, rígidos y dependientes de la observación humana manual. El objetivo de este trabajo, fue desarrollar, entrenar y validar el sistema denominado EBISU, un marco de software no invasivo para evaluar variables cinemáticas en vivo. Metodología: La investigación es de tipo tecnológica aplicada; se empleó una muestra experimental de tilapia (Oreochromis niloticus) en un entorno de recirculación controlado. Como instrumentos y técnicas se utilizaron cámaras digitales acopladas a nodos IoT, procesamiento de video en paralelo mediante PyQt5 y la arquitectura de aprendizaje profundo YOLO para la detección y seguimiento geométrico cuadro por cuadro. Resultados: Los resultados demostraron que el sistema procesa flujos de video fluidamente, determinando con precisión si las velocidades de nado indican parámetros normales o estrés metabólico. Discusión: Se destaca queEBISU supera la sustracción de fondo clásica al mitigar eficazmente reflejos lumínicos y turbulencias del agua. Conclusión: El sistema automatiza con éxito la supervisión biológica continua, reduciendo el error humano y sentando bases metodológicas para futuros trabajos en acuicultura de precisión en tiempo real.

Palabras clave: Aprendizaje profundo, YOLO v8, bienestar animal, monitoreo no invasivo.

Introduction

In the field of aquaculture, computer vision is emerging as a fundamental pillar for the transition to Aquaculture 4.0, enabling the non-invasive monitoring of living organisms in intensive production environments. In this regard, significant advances have been made, particularly in Asia, where such studies help strengthen food security in those countries given the region's predominant culinary culture (Biazi and Marqués, 2023; Liu et al., 2023; He et al., 2026; Ranjan, 2026).

However, the Mexican industry, at least in the northwestern region, lags behind in the adoption of these instrumentation technologies. The monitoring of culture tanks continues to rely on manual and empirical observation, which introduces critical errors from a control engineering perspective, including the inability to perform continuous monitoring, since the human eye cannot process visual signals without interruption, thereby preventing the detection of transient anomalous behaviors (Liu et al., 2023; Cui et al., 2025). Consequently, there is a lack of digitization of biological variables due to the absence of a real-time processing system that translates swimming patterns into quantitative data (angular velocity, stroke frequency, flow density), causing a significant delay between the onset of a problem and the activation of life-support systems (aerators or dosing pumps) and also resulting in the loss of vital information for the preventive diagnosis of diseases or hypoxic stress (Cai et al., 2024).

In this regard, it is worth noting that the impetus behind this particular project stemmed from a real-life catastrophic event that occurred at the

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experimental facilities of the Mazatlán Institute of Technology. A power outage disabled the aeration system in white shrimp tanks. Because the incident occurred outside of the monitoring window, the drop in dissolved oxygen was not detected in time, resulting in the suffocation and 100% mortality of the biomass under study. This could have been prevented had there been a system capable of triggering an alarm upon detecting changes that jeopardize production.

In general, the increasing intensification of aquaculture systems in the region has heightened the need to implement continuous monitoring mechanisms that ensure the welfare of farmed organisms and prevent production losses. In practice, fish monitoring continues to rely heavily on visual observation by human operators, who empirically assess variables such as swimming activity, feeding response, spatial distribution of the school, and the presence of abnormal behaviors (He et al., 2026). However, this approach has inherent limitations related to observer subjectivity, the inability to maintain constant surveillance, and the difficulty of detecting subtle behavioral changes in real time (Al-Abri et al., 2025).

In this context, computer vision-based monitoring systems have become one of the most promising technologies due to their ability to continuously and noninvasively obtain biological information (Biazi and Marqués, 2023). The digital transformation of aquaculture has given rise to the paradigm known as Aquaculture 4.0, which integrates smart sensors, the Internet of Things (IoT), artificial intelligence, and computer vision systems to optimize production, reduce economic losses, and improve animal welfare (Firzgerald et al., 2025).

Recent studies in precision aquaculture recognize that behavior is one of the most sensitive indicators of the physiological state of fish (Cai et al., 2024; Ahmed and Jeba, 2024; Liu et al., 2023). Changes in swimming speed, alterations in group cohesion, an increase in erratic trajectories, decreased motor activity, or changes in spatial interaction patterns often occur in response to stress, hypoxia, infectious diseases, poor water quality, or adverse environmental changes (Fitzgerald et al., 2025; Zhang et al., 2025). As a result, automated behavioral analysis has become one of the most significant lines of research within Aquaculture 4.0 (Cui et al., 2025).

From this perspective, the present study hypothesizes that swimming patterns can function as a digital behavioral biosensor capable of providing early indications of changes in the physiological state of fish before visible clinical signs or mortality events occur. In other words, variations in the kinematic characteristics of swimming patterns (speed, spatial dispersion, and locomotor activity) constitute early indicators of physiological stress in farmed fish and can be automatically detected using computer vision and deep learning techniques (Li et al., 2024). This hypothesis is based on the fact that aquatic organisms respond to environmental disturbances through observable changes in their locomotor activity, which can be objectively quantified using computer vision and artificial intelligence techniques (Cui et al., 2025).

Recent advances in fish behavior recognition using computer vision have demonstrated that kinematic variables such as speed, acceleration, trajectories, group dispersion, and movement frequency can be automatically extracted from video sequences and used to identify behaviors associated with feeding, stress, disease, and animal welfare (Al-Abri et al., 2025). These approaches make it possible to transform biological patterns—traditionally interpreted subjectively—into quantitative indicators suitable for computational analysis (He et al., 2026).

However, according to Fitzgerald et al., 2025, the adoption of these technologies remains limited in many production systems, particularly on small- and medium-scale farms. As a result, critical events associated with decreases in dissolved oxygen, aeration failures, deteriorating water quality, or pathological processes may go undetected for prolonged periods, especially during times without human supervision (Sun et al., 2025).

Given this scenario, there is a need to develop an intelligent electronic system based on computer vision that continuously monitors fish swimming patterns and translates these behaviors into objective indicators of biological risk. Automating this task would make it possible to replace intermittent monitoring with a continuous observation system capable of generating early warnings when significant deviations from normal farm behavior are detected, thereby helping to reduce economic losses, improve animal welfare, and strengthen the principles of smart and sustainable aquaculture (He et al., 2026; Cui et al., 2025).

Therefore, given this context, the work presented in this document was carried out. It consists of the development of an intelligent electronic system based on computer vision for the automated monitoring of aquaculture tanks, aimed at strengthening the productivity and sustainability of the aquaculture sector in the Mazatlán region of

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Sinaloa—a strategic area due to its importance to fishing and aquaculture activities in northwestern Mexico. The proposal integrates digital image processing, animal behavior analysis, and real-time electronic monitoring, enabling the identification of abnormal patterns in fish associated with disease, stress, or changes in water quality. Using cameras and visual analysis algorithms, the system provides continuous monitoring of the aquaculture operation, reducing reliance on manual supervision and facilitating more accurate and timely decision-making by the producer. Among the benefits of this system are reduced economic losses, optimized feed utilization, increased operational efficiency, and improved aquaculture production conditions. Similarly, it helps drive technological transformation in the primary sector, promoting a more competitive, sustainable, and innovative aquaculture model in line with Industry 4.0 trends as applied to the agri-food sector.

Methodology

The research was conducted using an experimental approach focused on the design and validation of a smart electronic system for the automated monitoring of aquatic organisms using computer vision. The proposed architecture, called EBISU, integrates deep learning techniques, object tracking, and behavioral analysis to identify variations in swimming patterns associated with potential states of physiological stress.

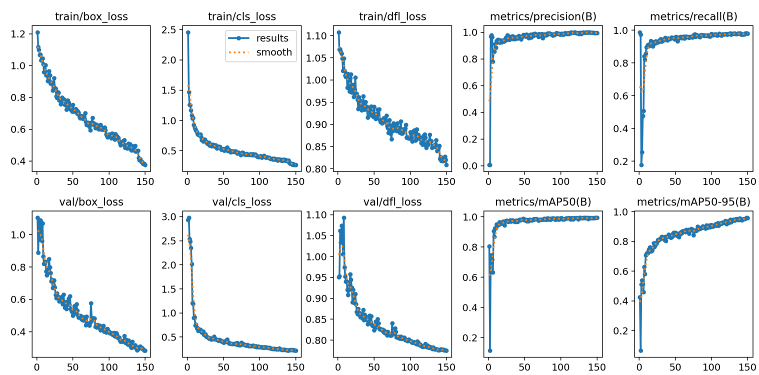
The methodology was structured into seven stages during the first semester of 2026: literature review, visual data acquisition, training dataset construction, automatic organism detection using convolutional neural networks, kinematic behavior analysis, early warning generation, and results analysis. This approach follows current trends in Aquaculture 4.0, where computer vision is used as a non-invasive tool for the continuous assessment of animal welfare (Biazi and Marqués, 2023).

When this project began, for practical reasons, we considered using stochastic computer vision approaches. This algorithm operates on the principle of "background subtraction." The camera assumes that the color of the tank water is static; if a drastic change in contrast occurs, the algorithm crops that cluster of pixels, assuming it is a moving organism (Bowmans, 2014). This methodology failed when applied to real-world farms. The water in production contains suspended organic matter (feces, feed) and dense columns of dynamic bubbles produced by the diffusers. The algorithm becomes confused, flagging the bubbles as invisible fish (false positives). This noise saturated the computer's memory and rendered the speed tracking inoperable.

Recognizing that background subtraction was a problem, Deep Learning using Convolutional Neural Networks (CNNs) from the YOLOv8 family was adopted. Convolutional matrices are immune to noise; they do not look for "moving colors," but rather evaluate biomorphic textures (fins, skull structure) that have been previously trained (Ranjan, 2026). In this way, the AI isolates correct visual detections and ignores the aeration.

For experimental validation, tilapia (*Oreochromis niloticus*) specimens reared in experimental ponds at the Mazatlán Institute of Technology were used. Tilapia was selected due to its widespread use in aquaculture systems in the region and its high resistance to variable rearing conditions. Digital cameras were installed above the tanks to capture video sequences representative of the system's operating conditions. Subsequently, frames were extracted from the obtained sequences, and the organisms were manually labeled using visual annotation tools. The creation of labeled datasets is a fundamental step in systems based on deep learning , as it allows models to learn the distinctive visual features of the organisms of interest and improve their ability to generalize under varying environmental conditions (Cui et al., 2025). The dataset shown in Figure 1 was divided into three independent subsets: training (70%), validation (20%), and test (10%), following best practices for developing computer vision models (Li et al., 2024).

Figure 1. Comprehensive model convergence plots. The decline in "Loss" (error) and the stabilization of the metric upon completion of iterative training can be observed.



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Automatic fish detection was initially performed using the YOLOv8 architecture, one of the most widely used object detection neural networks today due to its balance between accuracy and inference speed (Terven et al., 2023). The selection of YOLOv8 was based on recent studies reporting superior results in aquaculture applications related to fish counting, organism tracking, disease detection, and real-time behavior recognition (Li et al., 2024; He et al., 2026).

During the training process, the model iteratively adjusted its internal parameters through backpropagation of error using the training and validation datasets. Performance was evaluated using standard metrics employed in computer vision, including precision, recall, F1-score, and confusion matrix (Rivadeneira et al., 2024).

Once the organisms were detected in each frame, the coordinates corresponding to the geometric centroid of each individual were calculated. These coordinates were used as input for a tracking module responsible for associating the identity of each fish across consecutive frames. Tracking was performed by calculating Euclidean distances between successive positions, allowing for the reconstruction of individual trajectories and the estimation of kinematic variables associated with locomotor behavior (Cai et al., 2024).

Based on the obtained trajectories, behavioral indicators such as instantaneous speed, average speed, and spatial dispersion were calculated. Various studies have shown that these variables represent sensitive biomarkers of animal welfare and can be used for the early detection of states of stress, hypoxia, or disease (Fitzgerald et al., 2025; Sun et al., 2025).

The central hypothesis of this research posits that swimming patterns function as a digital behavioral biosensor capable of reflecting physiological alterations before the onset of visible clinical signs. Based on this premise, an analytical module was developed to identify deviations from the culture’s normal behavior. The system continuously evaluates the group’s average speed and inter-individual variability to detect two main conditions:

Lethargy or an abnormal decrease in locomotor activity.

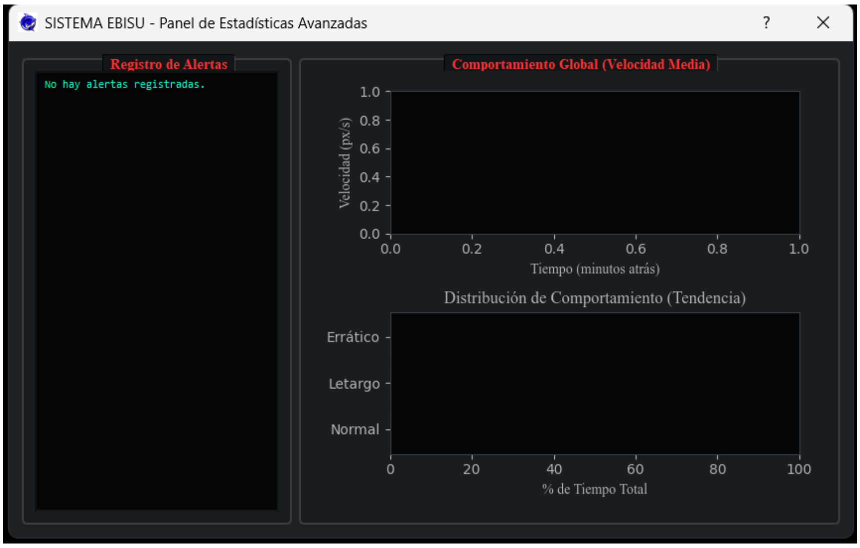
Erratic swimming or an abrupt increase in kinematic dispersion.

Both patterns have been reported in the literature as behavioral responses associated with physiological stress, deteriorating water quality, and hypoxia events (Fitzgerald et al., 2025; Zhang et al., 2025; Sun et al., 2025).

When behavioral variables exceed predefined thresholds, the system generates automatic alerts via remote messaging services (the Telegram app was used), thereby mitigating the risk of communication breakdowns on rural farms. The integration was designed with network exception handling. If an alert fails due to a lack of internet connectivity, the core architecture continues to process the data without “freezing” or causing a critical shutdown. It also incorporates a mathematical “cooldown” mechanism that prevents the repetition of identical alerts (to prevent spam on the on-duty biologist’s cell phone). This mechanism allows for timely notification of those responsible for the crop, facilitating the implementation of corrective actions before significant damage to the biomass occurs.

To synthesize the information into a real-time analytical format, parallel logic processors (PyQt5’s QThread) were used. This allows a complex interface to generate a statistics dashboard powered by Matplotlib (see Figure 4). This submodule compiles a history of 1,800 computational cycles of the tank in memory. It plots continuous curves that show the fluctuation of V_global relative to the lethargic danger threshold and, in parallel, displays distribution bars that calculate the overall percentage of operational time during which the test tank has remained in a normal, lethargic, or erratic state, thereby providing a massive data science framework.

Figure 2. Interactive console for species-specific parametric orchestration



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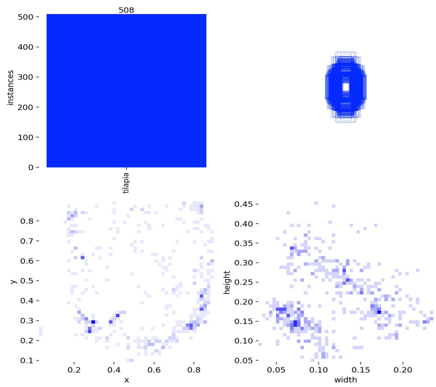
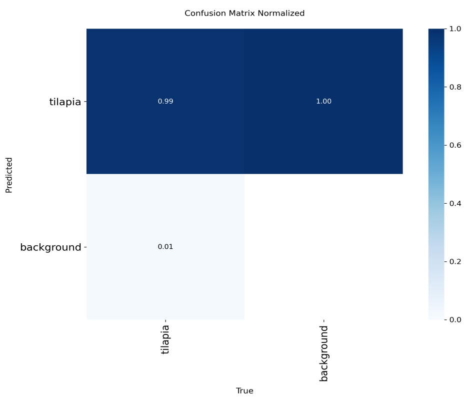
Similarly, to demonstrate that artificial intelligence eliminated the interferences present in the initial test algorithm, the graphs resulting from the pilot training were analyzed. The spatial distribution illustrated in Figure 3 shows how the test bed forced the network to discern specimens located at all bottom densities of the tank, thereby preventing biased memorization of photographic quadrants.

Figure 3. Spatial distribution of dataset labels showing positional vector densities within the visual matrix



Furthermore, the normalized confusion matrix shown in Figure 4 demonstrates perfect discrimination against the background (noise and bubbles). YOLOv8 refuses to assign biological identities to gaseous entities in the aeration column.

Figure 4. Normalized confusion matrix of the CNN algorithm



The peak of the F1 curve illustrated in Figure 5 reflects an optimal weighted index at a parametric confidence level of ~0.4 for the model, balancing the avoidance of false positives against the omission of false negatives.

Figure 5. F1 curve (F1-Score), determining the optimal balance between Precision (Positive Predictives) and Recall (Sensitivity).

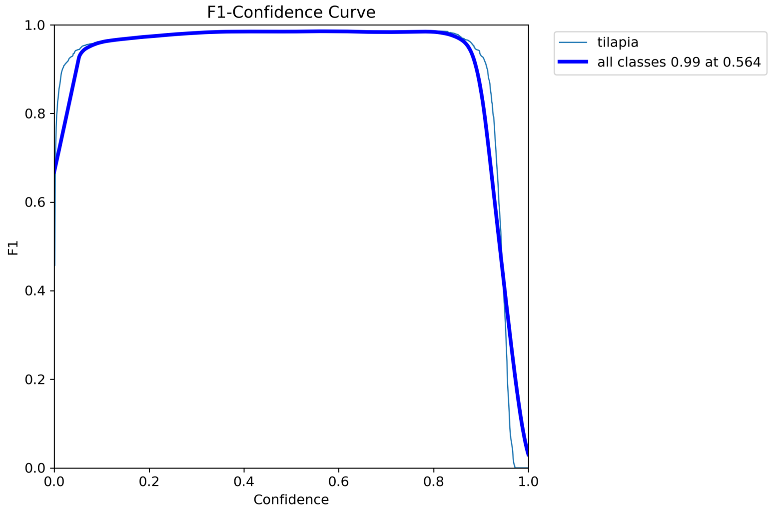
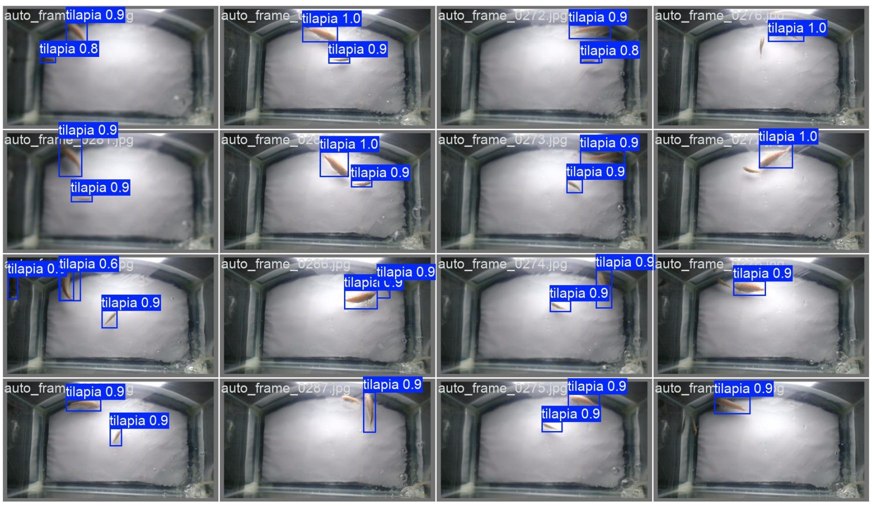


Figure 6 shows the automated extraction of the validation batch, where the algorithm isolates the instances without being corrupted by extraneous factors.

Figure 6. Automated extraction of the validation batch.



The system's performance was evaluated through tests conducted under real-world operating conditions. The analysis assessed the system's ability to detect organisms, the stability of tracking, the accuracy of behavioral analysis, and the system's robustness against complex

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environmental conditions such as the presence of bubbles, variations in lighting, and high biomass densities. The results obtained were compared using performance metrics employed in object detection and behavior recognition systems, allowing for an evaluation of the system's viability as a continuous monitoring tool for aquaculture applications.

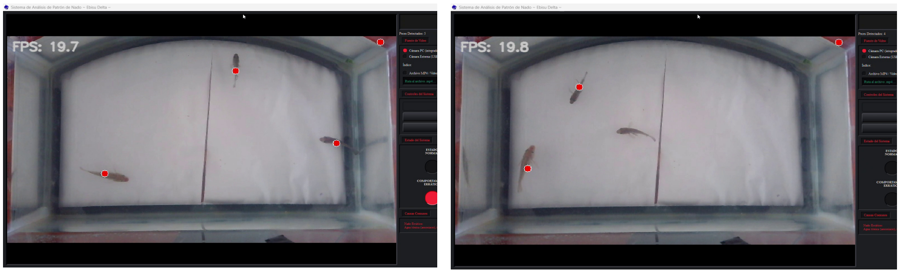
Results

The results obtained during the training of the YOLOv8 model demonstrated stable convergence of the loss functions associated with classification, localization, and object detection. The progressive decrease in loss values observed during the training iterations indicates that the neural network successfully learned the distinctive visual features of the organisms present in the dataset, gradually reducing the prediction error. The evolution of the performance metrics showed consistent behavior between the training and validation sets, suggesting adequate generalization ability of the model and a low tendency toward overfitting. These results are consistent with recent research that identifies YOLOv8 as one of the most efficient architectures for aquaculture applications requiring real-time organism detection under variable environmental conditions (He et al., 2026; Al-Abri et al., 2025).

Furthermore, the confusion matrix obtained during the validation stage demonstrated a high ability to distinguish between fish and environmental elements, particularly in the presence of visual interference caused by aeration bubbles, surface reflections, and suspended particles in the water. This result represents a significant improvement over traditional background subtraction methods, which tend to exhibit a considerable increase in false positives in dynamic aquatic environments (Terven et al., 2023).

Once the organisms were detected, the tracking algorithm based on centroids and Euclidean distance—as also noted in the study by García (2024)—allowed for the identification of individual organisms to be maintained across consecutive video sequences. The tests conducted demonstrated that the system was capable of reconstructing continuous trajectories even in situations of high population density and frequent interactions between organisms. The stability observed during tracking made it possible to obtain consistent time series of position and movement, an essential condition for the reliable estimation of behavioral variables. This can be seen in the images obtained from the system, which are illustrated in Figure 7.

Figure 7. In-Situ Validation of Continuous Tracking



a).- In-situ validation at the 5-second mark of continuous tracking.

b). Persistence of the Euclidean tracker navigating complex intersections (second 15).

In this regard, Fitzgerald et al. (2025) note that tracking accuracy is one of the most critical factors in automated animal behavior analysis systems, since association errors can propagate to subsequent stages of kinematic analysis. Therefore, based on the reconstructed trajectories, kinematic variables related to the fish's locomotor behavior were calculated, including instantaneous speed, average group speed, and spatial distribution of the school (Cui et al., 2025). These variables were analyzed continuously to identify deviations from behavior considered normal within the experimental system.

The results of the performance metrics (see Table 1) showed that the system was capable of detecting significant changes in the collective dynamics of the fish population by identifying patterns consistent with states of hyperactivity and lethargy. The scientific literature recognizes that these types of behavioral responses are often associated with physiological stress, decreases in dissolved oxygen, environmental disturbances, and early stages of disease (Sun et al., 2025; Zhang et al., 2025).

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Table 1. *Performance metrics of the EBISU detection model (YOLOv8)*

Performance Metric	Value (%)
Precision	96.2
Recall	94.8
Mean Average Precision (mAP@0.50)	98.5
Optimal F1-score	0.95

The integration of artificial intelligence-based early warning systems is one of the main areas of development in smart aquaculture, as it enables the transformation of large volumes of data into useful information for operational decision-making (Li et al., 2024).

The results suggest that the proposed architecture has the potential to be integrated into Aquaculture 4.0 frameworks focused on the smart monitoring of aquatic organisms. The combination of deep learning-based detection, automated tracking, and behavioral analysis provides a tool capable of transforming complex biological signals into objective indicators for decision-making.

Additionally, the modular nature of the system facilitates its adaptation to other aquaculture species by retraining the detection models while retaining the tracking and behavioral analysis algorithms. All kinematics, stress mathematics, telemetry, and underlying architecture will function without altering the base code, thereby consolidating a universal multispecies framework. This feature aligns with current research trends in digital aquaculture, which aim to develop scalable and reusable platforms for different production scenarios (He et al., 2026; Cui et al., 2025; Sun et al., 2025).

As a future project, the goal is to train the system using more advanced technologies—such as YOLO v11—to improve accuracy and sensitivity, among other parameters that may be of interest. This will require investing in equipment capable of processing the data optimally.

Conclusions

The system's ability to automatically quantify variations in fish movement supports the hypothesis that swimming patterns can be used as a digital behavioral biosensor. From this perspective, locomotor behavior ceases to be merely a qualitative observation made by human operators and becomes a continuous source of quantifiable information for assessing animal welfare.

One of the main findings of this research was the feasibility of implementing a continuous monitoring system without the need for constant human supervision. The system operated autonomously, processing video sequences in real time, calculating behavioral indicators, and generating automatic alerts when the analyzed variables exceeded established thresholds. This result is significant because one of the most important limitations of traditional aquaculture production systems is their reliance on intermittent visual inspections conducted by human personnel (Fitzgerald et al., 2025). Recent research highlights that computer vision systems constitute an effective alternative for increasing monitoring frequency, reducing errors associated with observer subjectivity, and improving responsiveness to critical events (Zhang et al., 2025; Sun et al., 2025).

The core value of this research lies in designing the software architecture under a unified, generic, and robust paradigm. EBISU has been demonstrated to function as an adaptable Universal Framework that allows researchers to completely disregard the specific test species. Simply compiling and substituting the neural weights will suffice to monitor a rainbow trout station or crustacean maturation, and the entire mathematical structure of Strikes, Thresholds, Vectors, visual data science, and HTTP telemetry will function properly.

This orchestration replaces the vulnerability of human biological monitoring (which is subject to error, fatigue, and nighttime interruptions) with a telemetric system. It qualitatively transforms the concept of aquaculture from prevention to real-time action protocols, thereby laying the logical and methodological foundations for the large-scale viability of 21st-century closed and intensive aquatic ecosystems. The results obtained demonstrate the technical feasibility of using computer vision and artificial intelligence to automate the behavioral monitoring of farmed fish and generate early-warning mechanisms that contribute to improving productivity, sustainability, and animal welfare in intensive aquaculture systems.

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