SINERGI Vol. 30, No. 1, February 2026: 197-208
http://publikasi.mercubuana.ac.id/index.php/sinergi
http://doi.org/10.22441/sinergi.2026.1.018

Development and performance evaluation of an automatic size-sorting system for catfish seeds using photodiode sensors

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Abstract
In catfish farming, uniform seed size is crucial for ensuring balanced growth and minimizing competition for feed. Generally, size sorting is performed manually through visual observation and net separation, which is labor-intensive, time-consuming, and often causes stress or injury to fish. To address these limitations, this study aimed to develop and evaluate a real-time, low-cost automatic sorting system for live catfish seeds. The proposed system utilizes photodiode sensors and an Arduino-based microcontroller to detect variations in fish body length by interrupting a laser beam. Four photodiodes were arranged at specific distances to classify fish seeds into four size categories (<7 cm, 7–8 cm, 9–10 cm, and 11–12 cm). After classification, the system automatically directed each seed into the corresponding container. The results showed that the prototype successfully classified and sorted catfish seeds with an overall accuracy of 67.5%. In contrast, tests with PVC pipes under controlled conditions achieved 100% accuracy. These findings highlight the novelty of integrating size detection and direct sorting for live fish seeds, a feature not previously reported in the literature. Beyond its current limitations, this system provides a methodological framework for sensor-based aquaculture automation, offering potential for further improvements in accuracy, robustness, and application to other aquaculture species.

Keywords:
Aquaculture;
Automatic sorting;
Catfish;
Photodiode sensor;

Article History:
Received: May 13, 2025
Revised: August 26, 2025
Accepted: October 4, 2025
Published: January 16, 2026

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INTRODUCTION

Catfish farming is one of the most promising freshwater fisheries sectors in Indonesia [1]. Based on data from the Ministry of Maritime Affairs and Fisheries of the Republic of Indonesia, in 2023, catfish cultivation production will be 1.13 million tons. With the increasing demand for catfish consumption, this cultivation activity is a promising economic opportunity for the community, especially in rural areas [2]. To maintain productivity and efficiency, paying attention to several technical aspects, such as fish growth, feed distribution, and efficiency in managing cultivation ponds, is necessary [3][4].

One of the significant challenges in catfish cultivation is the difference in the size of fish seeds or seedlings, which can cause larger individuals to dominate smaller individuals, thus creating an imbalance in the competition for food [5][6]. In addition, catfish also have cannibalistic traits, so differences in size can increase the chances of cannibalism and reduce cultivation productivity [7, 8, 9] Therefore, periodically sorting catfish sizes is essential to maintain population uniformity and increase cultivation productivity [10].

The process of sorting catfish based on size commonly used today is still manual, using simple tools, such as trays that are given holes according to the size of the catfish to be sorted. This sorting process has several weaknesses, including taking a long time, depending on the operator's expertise, and potentially causing stress to the fish due to repeated physical handling. Technological solutions that are more efficient and accurate and help reduce dependence on manual labor are necessary to increase cultivation productivity.

Several researchers have reported various approaches to predict fish size using image processing and automatic fish counting. However, automatic fish seed classification technology, especially for catfish, is still very limited. [11] has reported an automatic fish sorting system based on machine vision equipped with a stereo camera to identify fish size in real time and direct the fish to the sorting gate at the end of the conveyor. [12] developed a weight-based fish sorting device using a strain gauge sensor and Arduino Uno to classify fish into three size groups. [13] Developing a fish mass estimation model using image analysis based on Principal Component Analysis-Calibration Factor and artificial neural networks successfully applied a moment-invariant image processing algorithm to identify species and distinguish fish sizes in a polyculture system and showed a high correlation between digital images and fish mass and length. Meanwhile, [14] reported the development of an automatic tool for counting and classifying catfish seeds based on size using YOLOv8, MobileNetV2, and OpenMV camera. Although these methods show promising results, unfortunately in their development they require complex hardware, high costs, and controlled environmental testing, thus limiting their practicality in application and use for small-scale cultivation. Therefore, despite the availability of various advanced solutions, there is still a gap in the development of low-cost, real-time, and minimally invasive fish seed systems that are suitable for the needs of small and medium farmers.

Along with the development of sensor and microcontroller technology, which is supported by ease and affordability, opportunities have emerged to automate various processes in aquaculture [15, 16, 17] Low-cost components such as photodiodes, laser diodes, and Arduino are increasingly being explored in multiple applications, such as water quality monitoring and automatic feeding systems. With proper design and adaptation to field conditions, this technology can provide real solutions that are easy to implement, especially for small-scale fish farmers.

This study proposes an innovative real-time catfish seed sorting system based on photodiode sensors and an Arduino microcontroller, utilizing low-cost technology that minimizes human involvement. Unlike most existing low-cost approaches, which are limited to size estimation, counting, or weight prediction and still require manual transfer, the proposed system not only determines the size of live catfish seed but also directly and automatically sorts them into designated size groups. Vision-based sensors, while accurate, remain expensive and technically demanding for small-scale farmers. Previous non-vision studies rarely integrate direct sorting—especially for live seed, where handling stress is critical. To our knowledge, no prior research has reported the integration of real-time size detection and direct automated sorting specifically for live catfish seed. This integration is crucial in aquaculture because it reduces handling stress and potential mortality, while increasing operational efficiency.

In addition to practical implications, this report also provides methodological contributions. We propose a non-vision sensor framework that integrates three sequential processes: (i) body length detection via a laser-photodiode array (light beam interruption), (ii) size-based classification, and (iii) automated sorting directly into appropriate holding tanks. We then compare performance under controlled "ideal object" conditions using PVC pipes sized to the target category (achieving 100% accuracy) and under live fish conditions (overall accuracy of 67.5%). The differences between these two methods provide insight into how biological behaviour (swimming and irregular body posture) affects sensor-based detection accuracy and informs future refinements in aquaculture automation.

This study aims to: (1) design and implement a low-cost non-vision framework that integrates detection, classification, and sorting for live catfish seed; (2) evaluate the performance of real-time classification and sorting under controlled conditions (PVC) and live fish; (3) assess operational implications for hatcheries (reduced handling and post-sorting survival monitoring); and (4) articulate design considerations and ways to improve accuracy and robustness for broader aquaculture adoption.

METHOD

The prototype uses photodiode and laser diode sensors as a body length detection system [18] for fish seeds. The signal from the photodiode sensor was processed by Arduino Uno to control the movement of the servo motor, directing the path of fish seeds, whose length was already known, to the container according to their size category. This system was designed to sort the size of fish seeds into four categories: less than 7 cm, 7–8 cm, 9–10 cm, and 11–12 cm.

Material

The electronic components needed make this device readily available on the market in Indonesia at a low cost. The list of electronic components and their functions can be seen in Table 1.

Methods

Figure 1(a) shows a block diagram of the prototype of an automatic catfish seed sorter. This diagram explains the system architecture, consisting of three main parts: input, processor, and output. In the input section, there is a laser diode array and a photodiode array to detect the body length of catfish seeds. The detection data is sent to the processing unit (Arduino Uno), which functions as a Central Processing Unit (CPU) to run the classification algorithm to determine the fish seeds' body length category. As an output section, there is an LCD to display the classification results and a servo motor to move the sorting line to the container according to size. All of these electronic components work with a voltage of 5V.

Figure 1(b) shows the electronic circuit of the developed prototype. Four photodiodes are connected to the Arduino digital pins, each on pins 2, 3, 4, and 5. This photodiode module likely uses the PD204-6C type photodiode, which has the following specifications: spectral range of 400–1100 nm, peak sensitivity at 940 nm, response speed of 6 ns, and a maximum dark current of < 10 nA. This photodiode can detect laser light from a laser diode module with a wavelength of 685 nm.

Meanwhile, the four laser diodes are only connected to a 5V voltage source and ground without going through the control pin of Arduino, so the laser diodes will light up continuously as long as the prototype is in active (ON) condition, because it receives HIGH logic directly. Arduino digital pin 7 is used to send control signals to the servo motor to regulate rotational movement. The 2x16 character LCD module is equipped with an I2C interface for efficient use of pins, so it only requires a connection to analogue pins 4 and 5 on the Arduino as a data communication path. All components, including photodiodes, laser diodes, motors, and LCDs, get their power supply directly from an external 5V adapter, not from the Arduino output. This configuration was chosen to ensure that the current requirements of each component are met without disrupting the power supply to the microcontroller, so that system performance remains optimal. Consistent with [19], we employed dedicated external power supplies, rather than the microcontroller's 5 V rail—for each sensor, actuator, and display module, thereby preserving I/O integrity and maintaining stable computational performance of the microcontroller.

The automatic sorting of catfish seeds based on body length follows the logic flow shown in Figure 2(a). When the fish enters the sorting tube, the system starts monitoring the status of four optical sensors consisting of laser diodes and photodiode pairs. Each pair of laser diode and photodiode is positioned transversely to the direction of seed movement in the sorting tube, as shown in Figure 2(b). The distance between the laser-diode and photodiode pairs represents the classification length of the seeds. The number of photodiodes disturbed by the fish body is used to estimate the catfish's length. The detection process starts from photodiode-1; if the signal from photodiode-1 is disconnected (OFF) because catfish seeds block it, the system continues to check the status of other photodiodes sequentially.

Table 1. List components, and function of the developed prototype

Components	Functions
Arduino Uno	Central Processing Unit, controlling the flow of data and instructions
Laser diode KY-008	Light source to activate the photodiode.
Photodiode	Sensor to detect the light from the photodiode.
16x2 Character LCD display	Display notifications, status, or measurement results
Servomotor	To direct the path of fish seeds
Power adaptor	Voltage source to turn on the device
Project box	Device casing with size (7.5 cm x 10 cm x 3.5 cm)
PVC Pipe	Frame of developed prototype

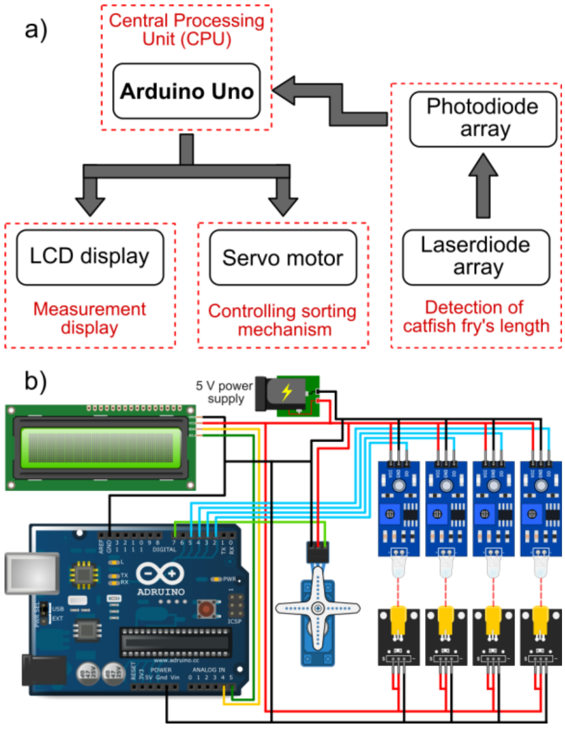

Figure 1. a) The block diagram, and b) the electronic circuits of the automatic catfish seed sorter prototype

The classification logic based on the number of photodiodes that are dead (OFF) is as follows:

- Only photodiode-2 is OFF (photodiodes-3 and -4 remain ON); The length of the fish seeds is around 7–8 cm
- Photodiodes-2 and -3 are OFF; The length of the fish seed is around 9–10 cm
- Photodiodes-2, -3, and -4 are OFF; The length of the fish seed is around 11–12 cm
- If only photodiode-1 is OFF (photodiodes-2, -3, and -4 are ON); The length of the seed is <7 cm

After the length of the catfish is identified, the system drives the servo motor to direct the fish to the appropriate sorting channel. The rotation angle of the servo motor based on the size category of the seed length is as follows:

- 30° for size < 7 cm
- 70° for size 7–8 cm
- 110° for size 9–10 cm
- 150° for size 11–12 cm

Because this study involves a multi-class classification problem (classes A–D), TP, FP, FN, and TN were defined in a one-vs-all manner for each class.

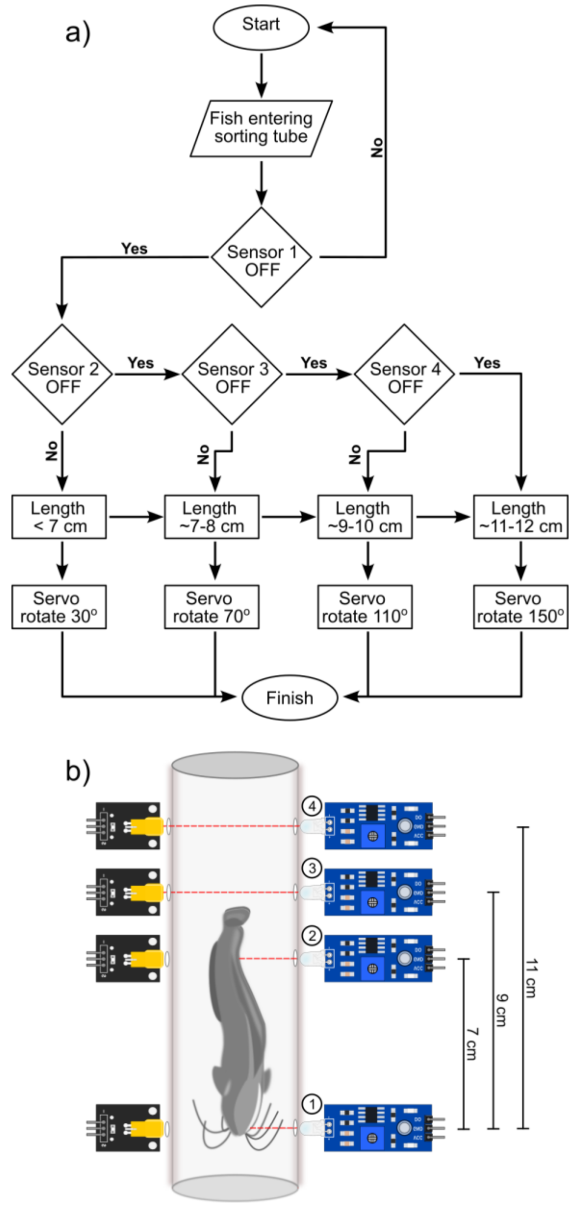

Figure 2. (a) Flowchart of catfish seed classification process based on body length using photodiode–laser diode sensor system and servo motor. b) Illustration of catfish seed sorting tube

For example, for class A (length < 7 cm), the definitions are:

- TP (True Positive): fish labeled as class A that are sorted into container C1.
- FP (False Positive): fish not labeled as class A but sorted into container C1.
- FN (False Negative): fish labeled as class A but sorted into a different container.
- TN (True Negative): fish not labeled as class A and not sorted into container C1.

The standard evaluation metrics per class are calculated using the equations in Table 2.

Table 2. Equation for calculating standard metrics per class

Metrics	Equation	Eq. No.
Recall/Accuracy	$\frac{TP}{(TP+FN)}$	(1a)
Precision	$\frac{TP}{(TP+FP)}$	(1b)
Specificity	$\frac{TN}{(TN+FP)}$	(1c)
*F*1	$\frac{2 \times Precision \times Recall}{(Precision + Recall)}$	(1d)

$$CI - Wilson = \frac{\hat{p} + \frac{z^2}{2n} \pm z\sqrt{\frac{\hat{p}(1-\hat{p})}{n} + \frac{z^2}{4n^2}}}{\frac{z^2}{n}}, \quad \hat{p} = \frac{x}{n} \tag{2}$$

For a 95% confidence interval, z was set to 1.96

To illustrate overall performance, an aggregation approach was used. The micro-average (overall) was calculated by summing all *TP*, *FP*, and *FN* values from all classes, and then computing Recall, Precision, and *F*1 based on this accumulation. The evaluation was conducted in a single-label, multi-class scenario, in which each sample had exactly one correct label and the system produced exactly one class prediction. In this scenario, micro-Precision, micro-Recall, and micro-*F*1 are identically equal to overall accuracy, since $(\sum TP + \sum FP) = (\sum TP + \sum FN) = N$. Therefore, we reported overall accuracy as a summary of the micro-metrics. The macro-average was calculated by averaging the scores per class, ensuring that all classes received equal weight, regardless of the number of samples.

For each proportion-based metric (Precision, Recall, Specificity, and Accuracy), a 95% confidence interval was calculated using the Wilson score interval method. These intervals provide more accurate lower and upper bounds than the normal approximation approach, especially for relatively small sample sizes (n = 10 per class). The *CI*-Wilson was defined by (2).

The results of the *TP*, *FP*, *FN*, and *TN* calculations for each class were presented in the Confusion Metrics Table. The evaluation metrics per class (along with confidence intervals) were presented in the Per-Class Metrics Table. A summary of the overall system performance was shown in the Global Metrics Table.

RESULTS AND DISCUSSION

The prototype of an automatic sorting system for catfish seeds using a photodiode–laser diode sensor and Arduino control has been successfully created. It can potentially replace the manual sorting process. This system aims to minimize human intervention to reduce stress on fish seeds during handling, while maintaining classification accuracy. The performance of the prototype was evaluated through a classification test of catfish seeds with varying body lengths, where its effectiveness was assessed based on its accuracy in grouping seeds into containers according to their respective size categories: <7 cm, 7–8 cm, 9–10 cm, and 11–12 cm [14].

Table 3 presents the confusion metrics resulting from the sorting process, showing the distribution of catfish fry across predicted classes (C1–C4) compared to their actual size categories (A–D). This metrics indicates that correct classifications occurred predominantly along the diagonal cells, while misclassifications were concentrated between adjacent classes, particularly from class B to A, class C to B, and class D to C.

To further analyze the classification results, Table 4 summarizes the *TP*, *FP*, *FN*, and *TN* values for each class using the one-vs-all scheme. The results show that class A (<7 cm) achieved the highest number of *TP* (10) without *FN*, while classes B, C, and D experienced *FN* errors, indicating challenges in distinguishing fish near the threshold length. The aggregate totals (27 *TP*, 13 *FP*, 13 *FN*, and 107 *TN* across all classes) provided the basis for calculating the evaluation metrics presented in Tables 5 and 6.

Table 5 shows the per-class evaluation metrics derived from the confusion values in Table 4. The system successfully classified all individuals in the <7 cm size category, with Recall = 1.00 [0.72–1.00] and F1 = 0.80, although the Precision value was slightly lower (0.67 [0.42–0.85]) due to the presence of fish from larger classes that were incorrectly assigned to this category. This finding indicated that the beam-break logic was reliable when only the first photodiode was blocked and the other three remained unblocked.

Performance decreased in adjacent categories. For the 7–8 cm group, Recall dropped to 0.50 [0.24–0.76] and *F*1 to 0.56, with Precision 0.63 [0.31–0.86]. For the 9–10 cm group, Recall was 0.70 [0.40–0.89], Precision was 0.58 [0.32–0.81], and *F*1 was 0.64. The 11–12 cm group exhibited high Precision (1.00 [0.57–1.00]) and Specificity (1.00 [0.89–1.00]), but Recall remained low (0.50 [0.24–0.76]), resulting in an *F*1 of 0.67. This concentration of misclassification around the boundaries between categories was consistent with the limited spatial resolution of the four-beam geometry relative to class width, as well as the variability in posture/orientation and swimming speed as fish passed through the tube.

In the one-vs-all scheme, Specificity per class remained high (0.83–1.00), indicating that the system rarely assigned fish from other classes to a particular class. However, accuracy per class varied between 0.80 and 0.88, reflecting errors primarily at class boundaries.

In aggregate, the prototype achieved an overall accuracy of 67.5% [0.52–0.80], which was identical to the micro-Precision, micro-Recall, and micro-*F*1 values in this single-label multiclass scenario. The macro-averaged scores across all classes were Precision = 0.72, Recall = 0.68, Specificity = 0.89, and *F*1 = 0.67, which confirmed consistent though not perfect performance across all classes.

To better isolate sensing/sorting performance from biological factors, we benchmarked the system using PVC pipes sized to the target categories. We obtained 100% accuracy, confirming that the photodiode-based detection and actuation mechanism functions reliably under behaviour-free conditions. The reduced accuracy in live trials is therefore attributed mainly to variability in swimming motion and body posture, rather than sensor limitations. This work is positioned as a low-cost feasibility study: we deliberately adopt an interpretable, on-device thresholding scheme compatible with Arduino-class hardware and small-holder constraints. In practice, the device can serve as a pre-sorting stage, reducing labor and fish stress, with brief manual refinement if necessary. Channel design adjustments and decision rule refinements are planned for future work to improve live-fish accuracy further.

As a benchmark against previously reported studies, we compare the photodiode beam-break approach with two families of solutions: camera-based machine vision/learning (MV/ML) and non-MV/ML systems (load-cell/strain-gauge or simple optics). Table 7 (MV/ML) and Table 8 (non-MV/ML) summarize representative studies, detection targets, detection methods, hardware components, and reported performance. MV/ML systems achieve higher accuracy under controlled optical conditions. However, they require cameras, lighting, and computation; by contrast, non-MV/ML systems offer low-cost options for mass measurement/counting but do not measure length directly.

Compared with MV/ML systems, the developed photodiode–laser (beam-break) system is positioned as an affordable, low-stress baseline for catfish seed, with minimal, low-cost hardware, a simple workflow, and end-to-end automation (detection → classification → routing). This system not only determines size but also separates fish directly based on size and can certainly be scaled up to count individuals within each size classification category. Unlike reported systems that only measure size, count, or estimate weight, this system integrates a separation mechanism as a critical follow-up measure in fish farming. The achieved overall accuracy of 67.5% [0.52–0.80] (for four length classes) is indeed lower than MV/ML, but the trade-offs—cost, ease of adoption, and seed safety—make it a relevant solution for small- to medium-scale catfish aquaculture.

Moreover, there is room to improve accuracy without sacrificing simplicity, namely: (i) increasing the number and optimizing the geometry of beams to enhance length-threshold resolution, (ii) optical calibration/alignment and anti-overlap guards in the channel, (iii) when needed, light hybridization (e.g., adding a low-cost camera module for auxiliary verification) to close accuracy gaps under certain conditions.

Table 3. Confusion Metrics (Actual vs. Predicted)

Actual \ Prediction	C1/A	C2/B	C3/C	C4/D
A (<7 cm)	10	0	0	0
B (7–8 cm)	5	5	0	0
C (9–10 cm)	0	3	7	0
D (11–12 cm)	0	0	5	5

Table 4. Confusion (TP, FP, FN, TN) per Class

Class	TP	FP	FN	TN	Total Samples
A (<7 cm)	10	5	0	25	40
B (7–8 cm)	5	3	5	27	40
C (9–10 cm)	7	5	3	25	40
D (11–12 cm)	5	0	5	30	40
Total (one-vs-all, aggregate)	27	13	13	107	160

Notes: Each class was calculated using the *one-vs-all* scheme. The row “Total (one-vs-all, aggregate)” represents the sum of *TP*, *FP*, *FN*, and *TN* across classes (not a single confusion metrics.

Table 5. Per-Class Metrics (Value [CI Wilson 95%])

Class	Recall / Accuracy	Precision	Specificity	F1	Per-class Accuracy (1-vs-all)
A (<7 cm)	1.000 [0.722–1.000]	0.667 [0.417–0.848]	0.833 [0.664–0.927]	0.800	0.875 [0.739–0.945]
B (7–8 cm)	0.500 [0.237–0.763]	0.625 [0.306–0.863]	0.900 [0.744–0.965]	0.556	0.800 [0.652–0.895]
C (9–10 cm)	0.700 [0.397–0.892]	0.583 [0.320–0.807]	0.833 [0.664–0.927]	0.636	0.800 [0.652–0.895]
D (11–12 cm)	0.500 [0.237–0.763]	1.000 [0.566–1.000]	1.000 [0.886–1.000]	0.667	0.875 [0.739–0.945]

Note: Formula descriptions (for each class, one-vs-all scheme):
Precision = *TP* / (*TP* + *FP*); Recall = *TP* / (*TP* + *FN*); Specificity = *TN* / (*TN* + *FP*); Per-class Accuracy = (*TP* + *TN*) / Total.

Table 6. Aggregate metrics (values [95% Wilson CI])

Aggregate	Precision	Recall	Specificity	F1	Overall Accuracy
Micro / Overall	0.675 [0.520–0.799]	0.675 [0.520–0.799]	0.892 [0.823–0.936]	0.675	0.675 [0.520–0.799]
Macro (class average)	0.719 [NA]	0.675 [NA]	0.892 [NA]	0.665	—

Note: The macro-average represents the mean across classes; therefore, the Wilson CI cannot be applied.

Table 7. Literature-based comparison of camera-based machine vision/learning (MV/ML) approaches for fish size estimation and grading, methods, hardware, and performance.

Reference	Species/Setting	Method (Algorithm)	Components (Hardware) and Cost	Summary of results/findings and Metrics
Albuquerque et al., 2019 [20]	Fingerling (Pintado), counting	Classical CV: blob detection + Mixture of Gaussians + Kalman filter	**Hardware:** Video camera, PC Cost estimate: 275 USD	Automatic seeds-counting system; validated on real videos. Metrics: accuracy 97,4 %
Jayasundara et al., 2023 [21]	Multi-species (Indian Sardinella and the Yellowfin Tuna); quality grading	Deep Learning: FishNET-S/T architecture (CNN)	Camera, computer Cost Estimate 300 USD	Automated grading; high performance on test datasets. Metrics: accuracy 68,3 %
Tonachella et al., 2022 [22]	Seabream; sea cages (smart buoy)	CV + AI; stereo photogrammetry	Stereo camera on buoy, edge computing Cost Estimate 4000 USD	Non-invasive length/weight estimation in open sea. Metrics: accuracy 70 %
Sung et al., 2020 [23]	Flatfish; sorting conveyor	Classical image processing for length→actuator control	Low-cost webcam, conveyor, actuators Cost Estimate 400 USD	Low-cost camera-based real-time grader. Metrics: NA
Marrable et al., 2023 [24]	Multi-species; stereo BRUVS	Deep Learning for head–tail detection + stereo calibration	Stereo camera, workstation	Semi-automated length measurement with near-human accuracy. Metrics: accuracy 73.51%

Reference	Species/Setting	Method (Algorithm)	Components (Hardware) and Cost	Summary of results/findings and Metrics
López-Tejeida et al., 2023 [25]	Aquaculture; weight estimation	ML/CV (Haar cascade + regression model)	NIR camera, computer Cost Estimate 329 USD	Non-intrusive weight estimation using NIR imaging. Metrics: accuracy 92 %

Table 8. Literature-based comparison of non-ML systems (load-cell/strain-gauge and simple optical) for fish sorting/counting, methods, hardware, and performance

Reference	Species/Setting	Method (Algorithm)	Components (Hardware) and cost	Summary of results/findings and metrics
This Work	Classification based on length (beam-break), catfish seed sorting	Laser beam-break and photodiode	Photodiode + Arduino Cost estimate: 25 USD	Catfish seeds are sorted automatically based on length. Metrics: accuracy 65 %
Rossi et al., 2021 [26]	Seabream juveniles; dynamic weighing	Dynamic signal processing (filtering/compensation)	Load cell (strain gauge), HX711/ADC, Arduino, Bluetooth Cost estimate: 40 USD	Compare dynamic vs. static weight, low-cost platform for biomass. Metrics: accuracy 80 %
Basyir et al., 2024 [27]	Weight-based sorter prototype	Rule-based by weight; conveyor automation	Load cell + HX711, Arduino, sorting mechanics Cost estimate: 80 USD	Complete design/implementation equipped conveyor. Metrics: accuracy 99 %
Zhang et al., 2018 [28]	Ornamental fish; real-time counting	Threshold/transit time (non-ML)	Non-imaging optical (IR) + single detector Cost estimate: 100 USD	Real-time counting system without a camera; reliable & simple. Metrics: accuracy 70 %
Fuentes-Pérez et al., 2025 [29]	Fishway; traffic monitoring	Event detection + silhouette reconstruction	IR beam-break curtain (LED + photodiode), RPi/ESP32 Cost estimate: 400 USD	Design & initial validation of a flexible, open-source IR counter. Metrics: accuracy 70 %

There are still misclassifications, thought to be caused by various factors related to the limitations of the classification system and biological variations in the behavior of catfish seeds [30]. Body position is crucial in determining whether the fish seeds properly block the laser beam [31]. As is known, seeds do not always swim straight and can rotate or tilt when passing through the sorting tube. This behaviour will disturb the laser beam break pattern so that the photodiode status conditions may become inconsistent, leading to incorrect body length estimation. Another essential aspect that affects the detection process is the tilt of the selection tube of about 20° to the horizontal. This tilt is intended to help the movement of the seeds downward following gravity so that they can pass through the detection path at a relatively stable speed without additional mechanical propulsion. However, this tilt can also affect the accuracy if the seeds slide too fast or are not perpendicular to the sensor. The position of the fish that is tilted or not parallel to the sensor plane causes the laser beam to be blocked, which does not correlate with the actual length of the seeds, resulting in inaccurate classification. To mitigate these issues, several strategies can be applied in future development. Hardware refinements such as optimizing the tilt angle, adding pre-alignment channels, or increasing the number of sensor pairs.

Variations in the swimming or falling speed of the seeds also contribute to misclassification.

Faster-moving seeds may not trigger the sensors in the expected sequence. In such cases, the sensors only receive partial or unstable interference signals, which makes the detection logic prone to errors due to the threshold-based decision-making algorithm. This logic is quite compelling for basic classification, but it cannot handle cases of ambiguity or smooth size transitions. The use of Advanced decision-making methods such as fuzzy logic, probabilistic classifiers, or adaptive rules can provide greater tolerance to ambiguous occlusion patterns and narrow class boundaries [32, 33, 34]. Implementing such algorithms will reduce classification errors, especially between adjacent categories, and enhance the system's robustness under real-world aquaculture conditions.

From a functional standpoint, simple threshold-based logic allowed the Arduino to easily make decisions about which servo motors to drive to the correct outlets. Each input from the photodiode was processed in real time and mapped to one of four angular states of the servo motor rotation based on the combination of sensor states. The use of dedicated digital pins to read the status of the photodiode sensor and an external 5V power supply separate from the Arduino 5V output can maintain the stability of system operation and minimize current fluctuations, which often occur in microcontroller systems when several components are active simultaneously [19, 32, 35] This power supply configuration contributes to measurement consistency [36][37].

In addition to the things discussed above, the system's accuracy can be affected by external factors such as environmental lighting [19] and water turbidity in the sorting tube [38]. In real conditions in the field (cultivation location), these factors can vary more than in the laboratory environment, reducing detection accuracy. Therefore, the system's next version can consider optical protection or sensor calibration to ambient light intensity.

Despite its limitations, this prototype provides an automatic and non-contact method for classification. This system offers significant advantages over manual sorting, which is more time-consuming, requires more effort, and may damage seeds due to direct handling. Thus, the survival and growth of seeds after sorting can be improved [39][40]. The physical photo of the prototype in Figure 3 shows that this system can be built with cheap and readily available materials, such as PVC pipes. Thus, this technology can be adopted on a small to medium scale.

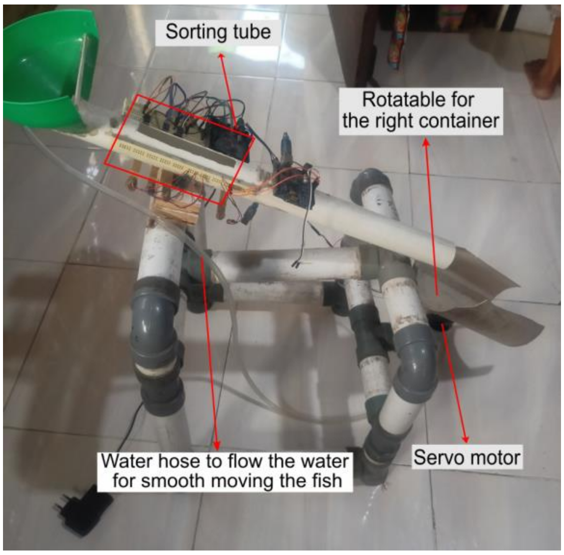

Figure 3. The photograph of the developed catfish seed sorting prototype

Several approaches can be pursued to improve classification accuracy in future development. One is to increase the number of sensor pairs, thereby refining size-detection resolution and reducing ambiguity at class boundaries. Another is to incorporate shape and orientation recognition by integrating optical sensors with image-based recognition systems, such as camera-based computer vision and OpenCV algorithms [41]. With recent advances in edge computing and the availability of low-cost microcontroller modules equipped with cameras or Raspberry Pi camera modules, this integration is increasingly feasible [42]. In addition, accuracy can be improved by adopting more advanced decision algorithms such as fuzzy logic, probabilistic classifiers, and adaptive rules. Such algorithms are expected to enhance system robustness under live-fish conditions. Ultimately, this technology provides a foundation for developing more precise and adaptive intelligent sorting systems for aquaculture. The system is also flexible, making it readily adoptable or customizable for other fish-seed species.

CONCLUSION

In conclusion, this study demonstrated a low-cost, non-vision-based framework that integrated real-time size detection, classification, and automated sorting for live catfish seed. To our knowledge, this was the first report to apply a laser–photodiode interruption scheme directly to live fish seed. This provided a methodological contribution in the form of a readily understandable workflow that was implemented on a microcontroller: beam interruption, size classification, and servo-driven sorting. The prototype was validated through both ideal object and live trials. This approach separated sensor/actuator reliability from biological variability, offering a reproducible evaluation protocol for future intelligent sorting systems.

In practice, this prototype could serve as a pre-sorting tool for small- to medium-scale aquaculture. It helped reduce labor requirements and handle stress, while improving operational efficiency. Future refinements to the channel geometry, adaptive decision rules, and hybrid sensing approach are expected to transform this proof-of-concept into a more precise and scalable intelligent sorting system, supporting precision aquaculture.

ACKNOWLEDGMENT

This research was supported by IPB University Division Grant for Applied Physics Division in 2023.

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