



ENHANCING UNDERWATER LIVE FISH DETECTION PERFORMANCE WITH YOLOV11 AND IMAGE ENHANCEMENT TECHNIQUES IN A REAL-TIME SYSTEM

PENINGKATAN KINERJA DETEKSI IKAN HIDUP BAWAH AIR MENGGUNAKAN YOLOV11 DAN TEKNIK PENINGKATAN CITRA WAKTU NYATA

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ABSTRACT

Underwater fish detection is challenged by low light, turbidity, and blue-green color dominance from light attenuation. This study aims to compare six image-enhancement scenarios (baseline, CLAHE, Retinex Ultra Lite, UDP, UDP Super Lite, and Gamma Correction + White Balance) combined with YOLOv11 to evaluate their detection accuracy and inference speed under challenging underwater conditions, and identify the most suitable method for real-time embedded underwater vision. Experiments used a controlled fish tank, filmed with an OAK-D camera under five natural lighting conditions (09:00–16:00 WIB). Performance was assessed qualitatively and quantitatively on a 600-frame test set (four illumination conditions), computing precision, recall, and mAP@0.5 from YOLOv11 predictions, plus inference speed in frames per second (FPS) on a Raspberry Pi 5 + OAK-D. CLAHE gave the best balance (precision 0.86, recall 0.83, mAP@0.5 0.84, 17 FPS); Gamma + White Balance was slightly less accurate (mAP@0.5 0.82) but faster (19.8 FPS); both outperformed the baseline (mAP@0.5 0.69, 21.3 FPS). Retinex Ultra Lite, UDP Super Lite, and full UDP all fell below 15 FPS (5.8–8.7 FPS), making them unsuitable for real-time edge deployment despite similar or lower accuracy. Lightweight, effective enhancement significantly improves real-time underwater fish detection on embedded devices, with CLAHE identified as the most suitable method for underwater object identification and quantification systems.

Keywords: CLAHE, fish detection, UDP, underwater image enhancement, YOLOv11

ABSTRAK

Deteksi ikan di bawah air menghadapi tantangan berupa pencahayaan rendah, kekeruhan, dan dominasi warna biru-hijau akibat peredaman cahaya. Penelitian ini bertujuan untuk membandingkan enam skenario peningkatan citra (*baseline*, CLAHE, Retinex Ultra Lite, UDP, UDP Super Lite, dan Gamma Correction + White Balance) yang dikombinasikan dengan YOLOv11 untuk mengevaluasi akurasi deteksi dan kecepatan inferensi pada kondisi bawah air yang menantang, serta mengidentifikasi metode yang paling sesuai untuk penerapan secara *real-time* pada sistem visi bawah air tertanam. Eksperimen dilakukan pada tangki ikan terkontrol, menggunakan kamera video OAK-D pada lima kondisi pencahayaan alami (09.00–16.00 WIB). Kinerja dinilai secara kualitatif dan kuantitatif pada data uji 600 gambar (empat kondisi pencahayaan), dengan menghitung presisi, *recall*, dan mAP@0.5 dari prediksi YOLOv11, serta laju bingkai inferensi (*frames per second*, FPS) pada Raspberry Pi 5 + OAK-D. CLAHE memberikan keseimbangan terbaik (presisi 0,86, *recall* 0,83, mAP@0.5 0,84, 17 FPS); Gamma + White Balance sedikit kurang akurat (mAP@0.5 0,82) namun lebih cepat (19,8 FPS); keduanya mengungguli *baseline* (mAP@0.5 0,69, 21,3 FPS). Retinex Ultra Lite, UDP Super Lite, dan UDP penuh berada di bawah 15 FPS (5,8–8,7 FPS), sehingga tidak sesuai untuk *real-time* pada perangkat tertanam. Peningkatan citra yang ringan namun efektif meningkatkan keandalan deteksi ikan bawah air *real-time* pada perangkat tertanam, dengan CLAHE sebagai metode paling sesuai bagi sistem identifikasi dan kuantifikasi objek bawah air.

Kata kunci: CLAHE, deteksi ikan, peningkatan citra bawah air, UDP, YOLOv11

INTRODUCTION

Underwater imaging and detection technologies are essential for identifying, quantifying, and managing aquatic resources, particularly in fishery stock assessments (Yusup *et al.* 2020; Wang *et al.* 2022). These systems are commonly implemented in autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) for ecosystem monitoring (Chan *et al.* 2022), where real-time deep learning-based detection is required for timely assessment of fish populations in their natural habitats (Li *et al.* 2018; Aruna *et al.* 2023).

The underwater environment degrades image quality through light scattering and absorption by suspended particles, which reduce visibility and depth perception and cause image blurring (Schettini and Corchs 2010; Powar and Wagdarikar 2017). This degradation hinders feature extraction by deep learning models, especially for small objects such as fish that occupy only a small portion of the frame, and causes conventional detection models to struggle (Papadakis *et al.* 2012; Lopez-Marcano *et al.* 2021). Real-time monitoring therefore requires high processing speed, expressed in frames per second (FPS), and low latency, which often must be traded off against detection accuracy, commonly measured as mean Average Precision (mAP) (Wang *et al.* 2022).

You Only Look Once (YOLO) is a family of single-stage object detection algorithms that localize and classify objects in a single forward pass through the network, offering a favorable balance between detection accuracy and inference speed (Khanam and Hussain 2024). This makes YOLO well suited for real-time deployment on embedded platforms such as the underwater vision system used in this study, where limited computational and memory resources remain a key constraint (Lu *et al.* 2020).

Previous studies on underwater fish detection have largely adapted YOLO-based detectors for real-time use on embedded platforms with raw footage, without addressing image degradation from turbidity and color attenuation (Amin *et al.* 2021; Chan *et al.* 2022). Separately, underwater image enhancement techniques such as CLAHE (Garg *et al.* 2018), Retinex (Tang *et al.* 2019), dark channel prior (Yang *et al.* 2011; Wu *et al.* 2021), and color-constancy correction (Muniraj and Dhandapani 2022) have been evaluated mainly with image-quality metrics such as contrast

and color fidelity, rather than by their effect on detection accuracy or inference speed on embedded hardware. Consequently, it remains unclear which enhancement method gives the best trade-off between detection accuracy and inference speed in a real-time embedded detection pipeline.

This study aimed to compare six image enhancement scenarios (baseline, CLAHE, Retinex Ultra Lite, Underwater Dark Prior (UDP), UDP Super Lite, and Gamma Correction with White Balance) integrated with YOLOv11 for underwater fish detection, in terms of detection accuracy and inference speed on a Raspberry Pi 5 and OAK-D camera, and to identify the most suitable method for real-time embedded underwater vision systems. The findings are expected to support low-cost, energy-efficient monitoring tools for fish stock assessment in the field.

METHODS

Time and location

This study was conducted at the Workshop of Marine Instrumentation and Robotics, Department of Marine Science and Technology, Faculty of Fisheries and Marine Sciences, IPB University, using a controlled fish tank measuring 1×2×0.5 m, stocked with two freshwater species of contrasting body coloration and pattern, Nile tilapia (*Oreochromis niloticus*) and koi (*Cyprinus rubrofascus*), as detection targets.

Data were collected on five separate days in June 2024, with one recording session per day at 09:00, 11:00, 12:00, 14:00, or 16:00 Western Indonesia Time (WIB) to represent natural variation in sunlight intensity and angle, from oblique morning light to softer afternoon light likely to be encountered during field operation. The tank, camera, and host computer setup is shown in Figure 1(a). Each session produced one continuous video of approximately five minutes, so the five videos came from independent recording sessions, with no repeated measurements at each time point.

Embedded system for real-time implementation

The real-time system developed in this study is designed for integration with the Underwater Televisual System (UTS). The technical specifications of the UTS

are summarized in Table 1. All test videos processed using the YOLOv11 object detection algorithm were executed within the UTS framework. The video frames were streamed to the host computer (Raspberry Pi), where selected image enhancement algorithms were applied. The enhanced frames were then sent back to the OAK-D camera for object detection. Finally, the detection results, which comprise the enhanced images with annotated bounding boxes (YOLOv11 output), were returned to the host computer. FPS measured in this study refers to the time required for one complete cycle of this workflow per frame.

Research design

This study was designed to investigate the effect of various image enhancement techniques on the performance of real-time underwater fish detection using the YOLOv11 algorithm. The research framework consists of three main stages: (1) Video data acquisition and preprocessing, (2) Application of image enhancement techniques, and (3) Training and evaluation of the YOLOv11 detection model, as illustrated in the workflow diagram in Figure 1(b).

Video data acquisition and preprocessing

The five videos obtained from the recording sessions described in the Time and Location section were used for model development and evaluation. Of these, the video recorded at 12:00 WIB, representing midday lighting, was designated as the training dataset and processed using five distinct image enhancement methods suitable for real-time underwater applications, resulting in six training videos: one original and five enhanced versions. The remaining four videos (09:00, 11:00, 14:00, and 16:00 WIB) represent the four experimental treatments used for testing and were reserved to evaluate model performance under different natural lighting conditions. For quantitative evaluation, each of the four test videos contributed 150 sampled frames containing tilapia and koi, yielding a pooled 600-frame test set that was used to compute precision, recall, and mAP@0.5 for every enhancement condition, in addition to inference frame rate (see Detection Performance Evaluation).

Image enhancement methods

Five image enhancement techniques were employed in this study to improve the

quality of underwater imagery:

1. CLAHE (Garg *et al.* 2018)

Contrast Limited Adaptive Histogram Equalization (CLAHE) was used to locally enhance contrast in color images. The process begins by converting the image to the LAB color space. The luminance channel (L) is processed using CLAHE with a clip limit of 1 and a grid size of 3×3. This method enhances local details in dark regions without significantly amplifying noise.

2. Retinex Ultra Lite (Tang *et al.* 2019)

This method simulates human visual perception by comparing the pixel intensity of the original image with a Gaussian-blurred version ($\sigma = 15$). The image is first converted to grayscale, then the ratio between the original and blurred images is computed and normalized to the 0–255 intensity range. This technique enhances texture details, especially in the blue channel (B), which typically suffers the most degradation in underwater environments.

3. Underwater Dark Prior (UDP) (Wu *et al.* 2021)

UDP is based on the assumption that dark pixels contribute most to underwater noise. It computes the minimum value across the RGB channels to estimate a transmission map, which is then used to correct pixel intensity. The transmission is constrained within the range of 0.3–0.9 to maintain visual stability. The result is an image with improved clarity and contrast.

4. UDP super lite (Yang *et al.* 2011)

This is a lightweight variant of the full UDP method. Instead of using the minimum RGB channel, it utilizes the maximum channel value as the basis for illumination estimation. The division result is used to enhance object visibility more efficiently, albeit with lower accuracy compared to the full UDP implementation.

5. Gamma correction + white balance (Muniraj and Dhandapani 2022)

This combined technique aims to brighten dark areas and achieve a more natural color balance. Gamma correction is performed by constructing a lookup table (LUT) based on a gamma value (default: 1.5), which maps pixel intensity using an inverse exponential function. This improves object visibility in darker regions without overexposing bright areas. Prior to gamma correction, white balance is applied to counteract the color cast caused by the selective attenuation of light wavelengths underwater.

Table 1. Technical specifications of the Underwater Televisual System (UTS) used for real-time implementation.

Component	Specification
Instrument	Underwater Televisual System (UTS), developed by the Workshop of Marine Instrumentation and Robotics, Department of Marine Science and Technology, FPIK IPB University
Camera	OAK-D camera with 1.4 TOPS of on-device AI processing capability
Host computer	Raspberry Pi 5 with 8 GB RAM
Software framework	DepthAI

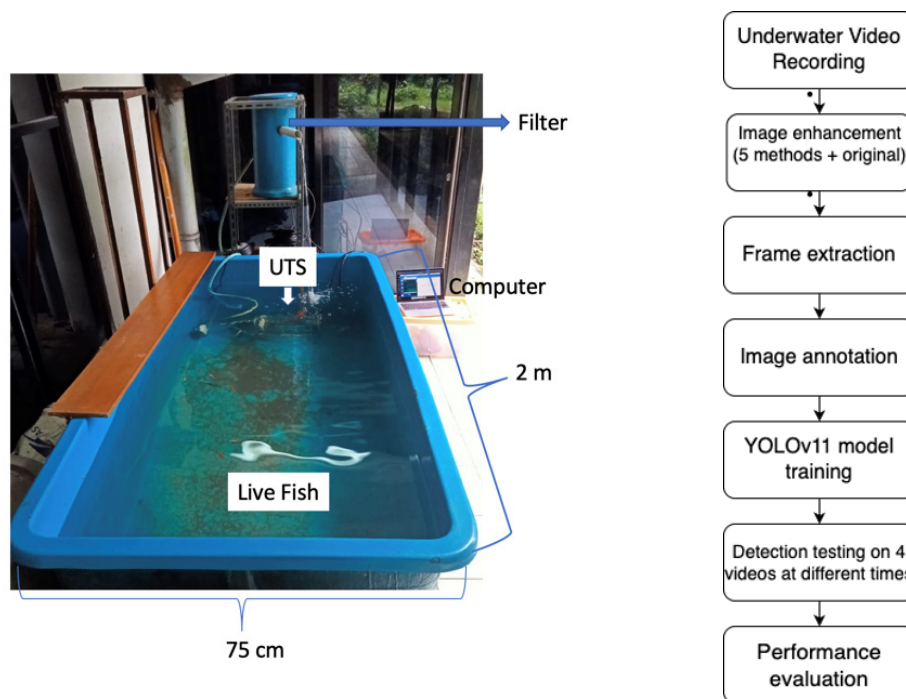


Figure 1. (a) The fish tank positioned in an open area with sunlight coming from the side, the UTS camera, host computer, and the five daily recording sessions (09:00, 11:00, 12:00, 14:00, and 16:00 WIB); (b) research workflow diagram.

Including the original (unenhanced) video, a total of six training video variants were generated. All videos were decomposed into individual frames, yielding a total of 600 images comprising 25% of frames from the original video and 15% from each of the five enhanced versions. All images were manually annotated using the Labelling tool to prepare the dataset for object detector training.

YOLOv11 model training

We used the annotated image dataset to train the YOLOv11 model, the latest version in the You Only Look Once (YOLO) object detection series, known for high accuracy and real-time performance. Compared with earlier YOLO versions, YOLOv11 introduces architectural refinements, including the C3k2 backbone block, an improved Spatial Pyramid Pooling-

Fast (SPPF) module, and a Convolutional block with Parallel Spatial Attention (C2PSA), which enhance feature extraction while keeping the parameter count low (Khanam and Hussain 2024). The model was configured with an input resolution of 416×416 pixels and trained for 150 epochs using Stochastic Gradient Descent (SGD) with a learning rate of 0.001. Training took place in PyTorch in a Google Colab environment, using GPU acceleration. To improve the model's robustness in various underwater conditions, the training dataset included six video variants: one original (unprocessed) and five enhanced versions (CLAHE, Retinex Ultra Lite, UDP, UDP Super Lite, and Gamma + White Balance). This diverse range of inputs significantly enhanced the model's ability to generalize across different lighting and visibility conditions typically found in underwater environments.

Detection performance evaluation

The trained YOLOv11 models were evaluated using four test videos recorded at 09:00, 11:00, 14:00, and 16:00 WIB to assess their performance under varying natural lighting conditions. Each video was processed with six different models, corresponding to the original and five enhanced versions of the training dataset. This facilitated a comparative analysis of the impact of each image enhancement technique on detection quality. For each of the six enhancement conditions, detection performance was additionally quantified on the pooled 600-frame test set (150 frames per illumination condition) using YOLOv11 horizontal bounding box (HBB) predictions.

The evaluation covered two aspects: detection performance and processing speed, and their overall suitability for real-time applications. Detection performance was quantified using precision, recall, and mAP@0.5, computed by comparing YOLOv11 HBB predictions against the manually annotated test-set labels for each of the six enhancement conditions, whereas processing speed was expressed as FPS. In parallel, detection effectiveness was also assessed qualitatively through visual inspection of the accuracy and consistency of fish identification in each frame, providing a complementary check on the quantitative metrics. Real-time viability was evaluated based on the ability of each model to maintain a balance between detection quality and speed, using a minimum inference rate of 15 FPS as the practical cut-off for real-time edge deployment. Bounding box outputs were visually compared across models to assess stability and clarity under different lighting conditions, aiding in the determination of which enhancement method yielded the most reliable results for underwater object detection. The full quantitative comparison across all six enhancement conditions is presented in Table 3 in the Results and Discussion section.

RESULTS AND DISCUSSION

Figures 2 to 5 illustrate the object detection outcomes using the YOLOv11 model on the four test videos recorded at 09:00, 11:00, 14:00, and 16:00 WIB, representing the four experimental treatments used to evaluate model performance under varying natural lighting conditions (the 12:00 WIB dataset having been reserved for model training, as described in the Methods section). Each figure presents the detection results across six distinct conditions:

original (without enhancement), Gamma Correction + White Balance, CLAHE, Retinex Ultra Lite, Underwater Dark Prior (UDP), and UDP Super Lite.

Visual observations indicated that underwater image quality was significantly influenced by the time of day, correlating with the intensity of natural light penetrating the water. In the videos captured at 09:00 and 11:00 (Figures 2 and 3), fish objects were comparatively easier to detect, particularly after enhancements using CLAHE and Gamma + White Balance. CLAHE consistently improved contrast and texture, aiding the model's ability to differentiate fish from turbid backgrounds. In contrast, Gamma + White Balance produced more balanced and natural coloration, though it occasionally resulted in oversaturation.

Conversely, the videos recorded at 14:00 and 16:00 (Figures 4 and 5) showed visibly reduced ambient lighting, leading to suboptimal detection performance with unenhanced (original) data. The model frequently struggled to identify objects due to low contrast and predominant blue tones. Under these conditions, CLAHE and UDP substantially enhanced detection. CLAHE improved object-background separation, while UDP effectively reduced underwater haze and enhanced object visibility. However, UDP exhibited issues with color instability and uneven brightness distribution, potentially leading to false positives in detection.

Retinex Ultra Lite produced inconsistent results depending on water type and lighting conditions. While it enhanced texture details, it also introduced significant color distortion, particularly during midday to afternoon periods (Figures 3 and 4). Although UDP Super Lite was computationally efficient, it was less effective in substantially improving visual quality and failed to facilitate detection in low-light conditions.

Table 2 compares six image enhancement techniques used in the YOLOv11-based underwater fish detection system, focusing on working principle, visual enhancement results, computational complexity, processing speed (FPS), impact on detection performance, and suitability for real-time applications. Following common practice in the embedded computer-vision literature, a minimum of 15 FPS was used as the reference threshold for real-time viability (Lee and Hwang 2022), against which the "Suitable for Real-Time?" column in Table 2 was judged. The "Impact on YOLO Detection" column reflects a qualitative, visual assessment rather than a quantitative accuracy metric, consistent with the evaluation approach described in the Methods section. The baseline

method without enhancements achieved the highest processing speed (19–23 FPS) but was inadequate for reliable detection in low-contrast, turbid, or dark underwater environments, underscoring the need for enhanced visual input for consistent fish identification.

The CLAHE method significantly improved contrast and texture details, maintaining a processing speed of 16–19 FPS, which is acceptable for real-time systems. Its positive impact on YOLO detection accuracy, especially in turbid conditions, positions it as one of the most optimal methods in terms of accuracy and efficiency.

The Retinex Ultra Lite method provided moderate contrast enhancement but introduced significant color distortion, particularly in certain water types. Its relatively complex

computations resulted in lower processing speeds (8–9 FPS), making it less suitable for real-time applications. Detection efficacy was highly dependent on lighting conditions and water color, leading to inconsistent performance.

The UDP and UDP Super Lite methods were developed to address underwater haze effects. While UDP improved detection in hazy conditions, its reliance on dark channel computation and spatial erosion caused a marked decrease in processing speed (5–6 FPS). UDP Super Lite achieved a slightly better speed (7–8 FPS) but suffered from reduced detection accuracy due to limited robustness against color noise. Both methods are unsuitable for real-time systems due to their computational demands and inconsistent performance.

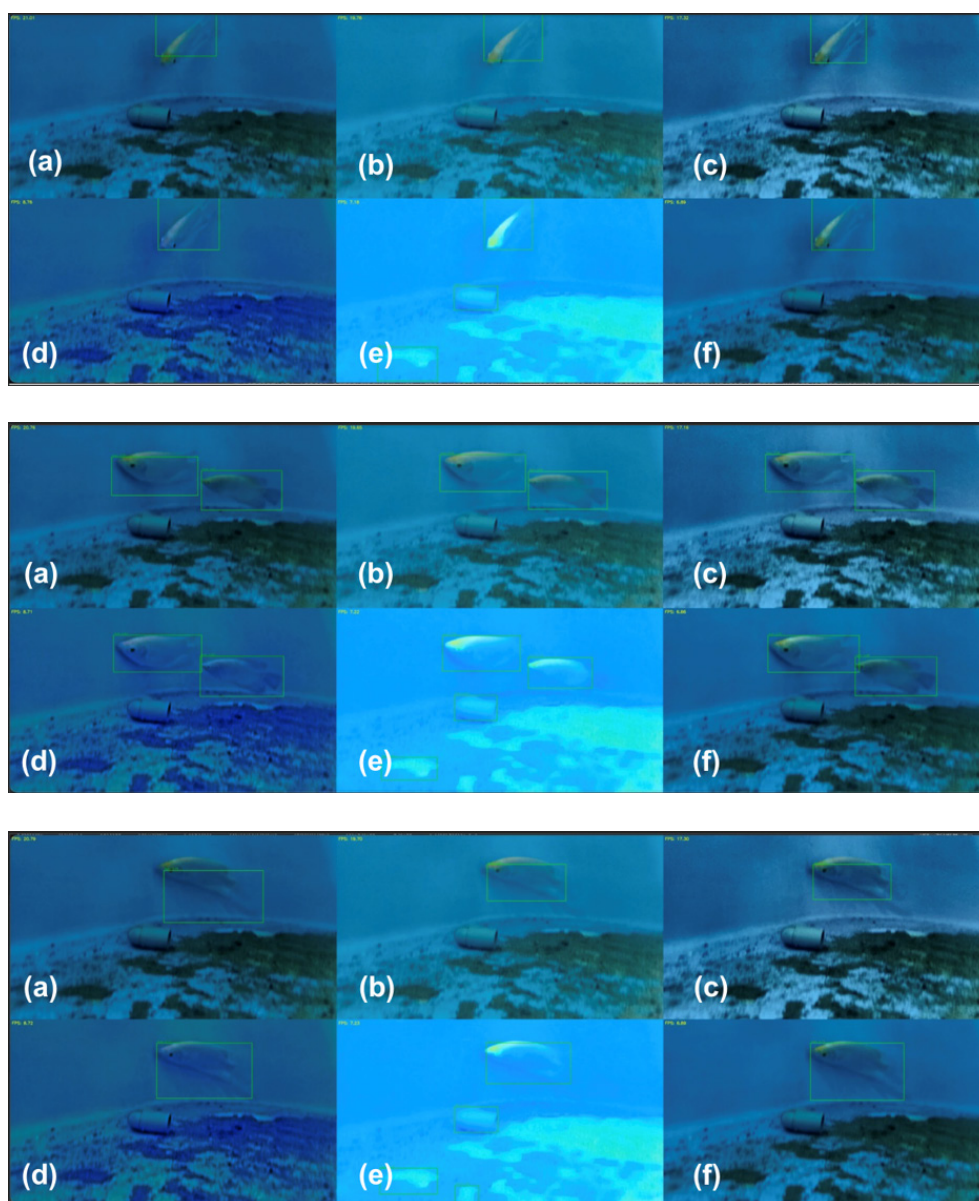


Figure 2. Sample detection results from the video recorded at 09:00 WIB: (a) Original, (b) Gamma and White Balance Correction, (c) CLAHE, (d) Retinex Ultra Lite, (e) UDP, and (f) UDP Super Lite.

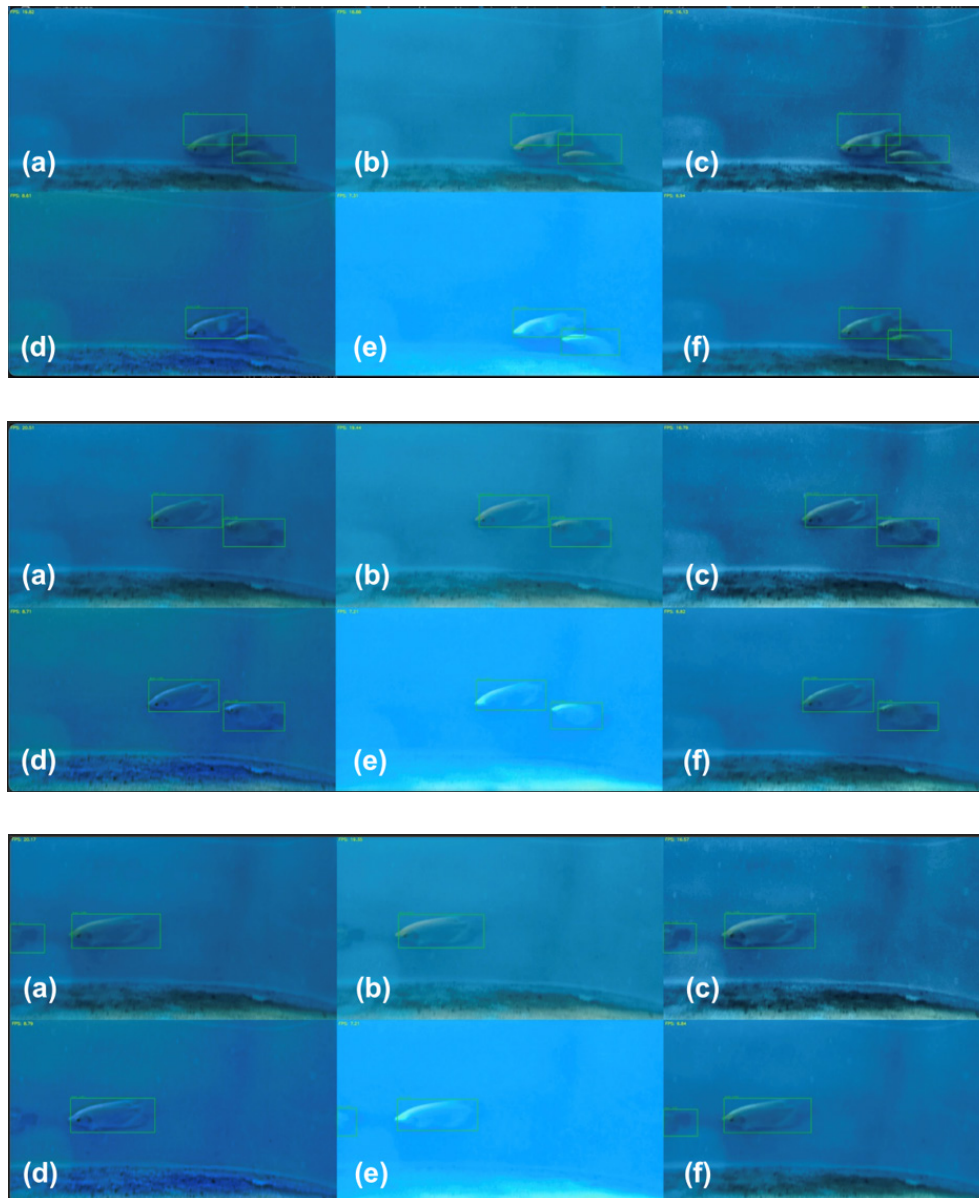


Figure 3. Sample detection results from the video recorded at 11:00 WIB: (a) Original, (b) Gamma and White Balance Correction, (c) CLAHE, (d) Retinex Ultra Lite, (e) UDP, and (f) UDP Super Lite.

In contrast, Gamma Correction with White Balance offered the best balance between processing speed and visual enhancement. With low complexity and a processing speed of 19–20 FPS, this method produced more natural visuals. Though it occasionally led to oversaturation in some regions, YOLO detection outcomes improved in darker conditions, making it suitable for real-time deployment, particularly on resource-constrained platforms like the Raspberry Pi or OAK-D. CLAHE and Gamma + White Balance demonstrated the most effective performance for real-time YOLOv11-based fish detection systems, providing substantial visual enhancement while maintaining manageable computational complexity for embedded systems. In contrast, high-complexity methods

such as UDP and Retinex Ultra Lite produced favorable visual results under specific conditions but were deemed unsuitable for real-time implementation due to a considerable decrease in frame rate (5–9 FPS).

To complement the qualitative assessment above, precision, recall, and mAP@0.5 were computed for each of the six enhancement conditions using YOLOv11 horizontal bounding box (HBB) predictions on a 600-frame test set drawn from the four test videos (150 frames per illumination condition), comprising both tilapia and koi. Inference frame rate was measured on the same Raspberry Pi 5 + OAK-D platform described in Table 1. These results, evaluated against a minimum of 15 FPS as the practical cut-off for real-time edge

deployment, are summarized in Table 3.

Table 3 confirms and quantifies the qualitative pattern observed above. CLAHE achieved the highest mAP@0.5 (0.84) among all six conditions while sustaining 17 FPS, above the 15 FPS real-time cut-off, and was therefore selected as the enhancement method for the proposed pipeline. Gamma + White Balance was a close second in accuracy (mAP@0.5 0.82) and delivered the highest frame rate among the enhanced conditions (19.8 FPS), making it an attractive alternative when inference speed is prioritized over the last few points of accuracy. The unenhanced baseline recorded

the highest raw frame rate (21.3 FPS) but the lowest accuracy of all conditions (mAP@0.5 0.69), confirming that raw underwater frames are insufficient for reliable YOLOv11 detection. Retinex Ultra Lite, UDP Super Lite, and full UDP all fell below the 15 FPS threshold (5.8–8.7 FPS) and did not exceed the accuracy of CLAHE or Gamma + White Balance, so despite their theoretical enhancement value, they are impractical for real-time edge deployment on the Raspberry Pi 5 + OAK-D platform. These quantitative results are consistent with, and reinforce, the visual assessment reported earlier in this section and in Table 2.

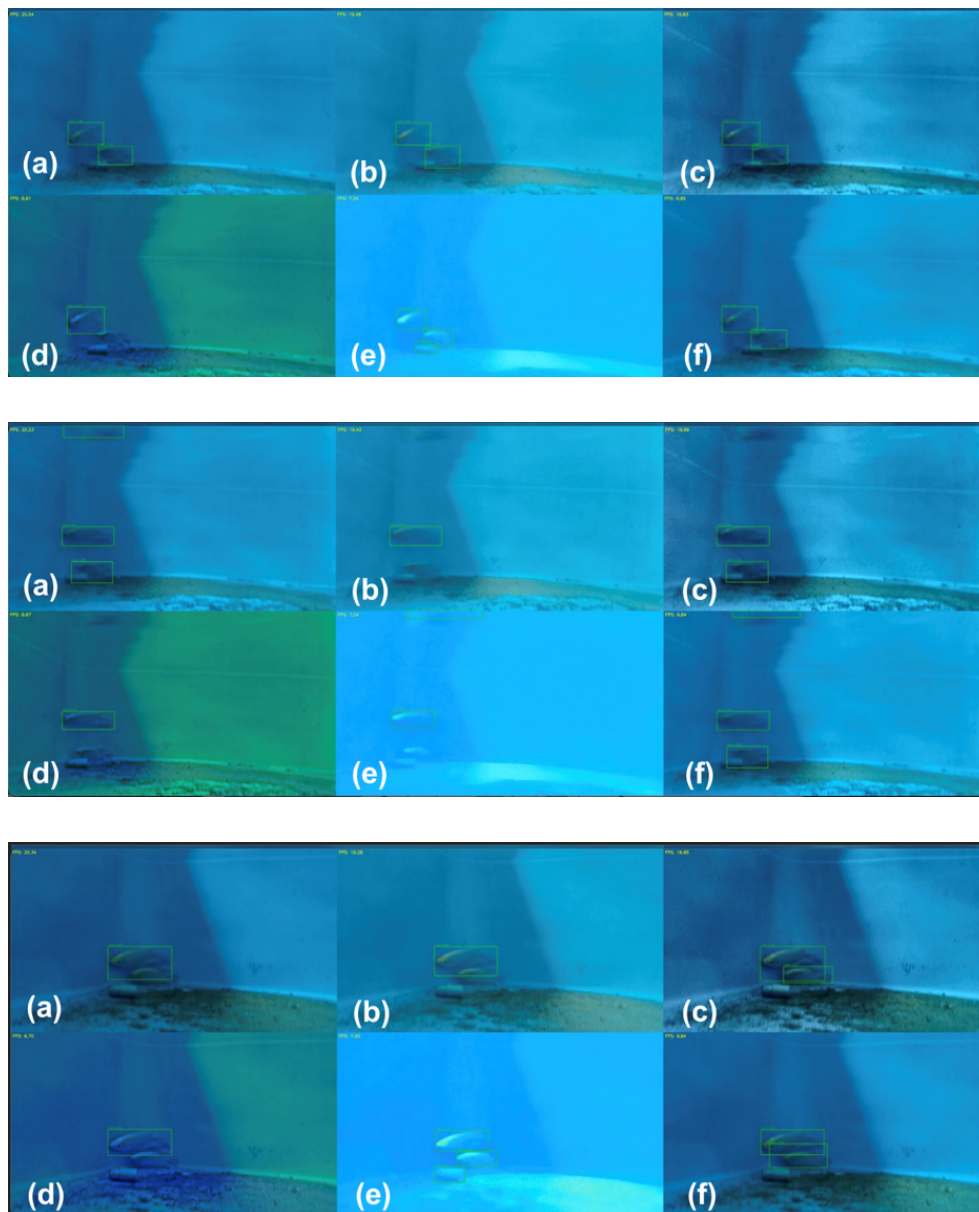


Figure 4. Sample detection results from the video recorded at 14:00 WIB: (a) Original, (b) Gamma and White Balance Correction, (c) CLAHE, (d) Retinex Ultra Lite, (e) UDP, and (f) UDP Super Lite.

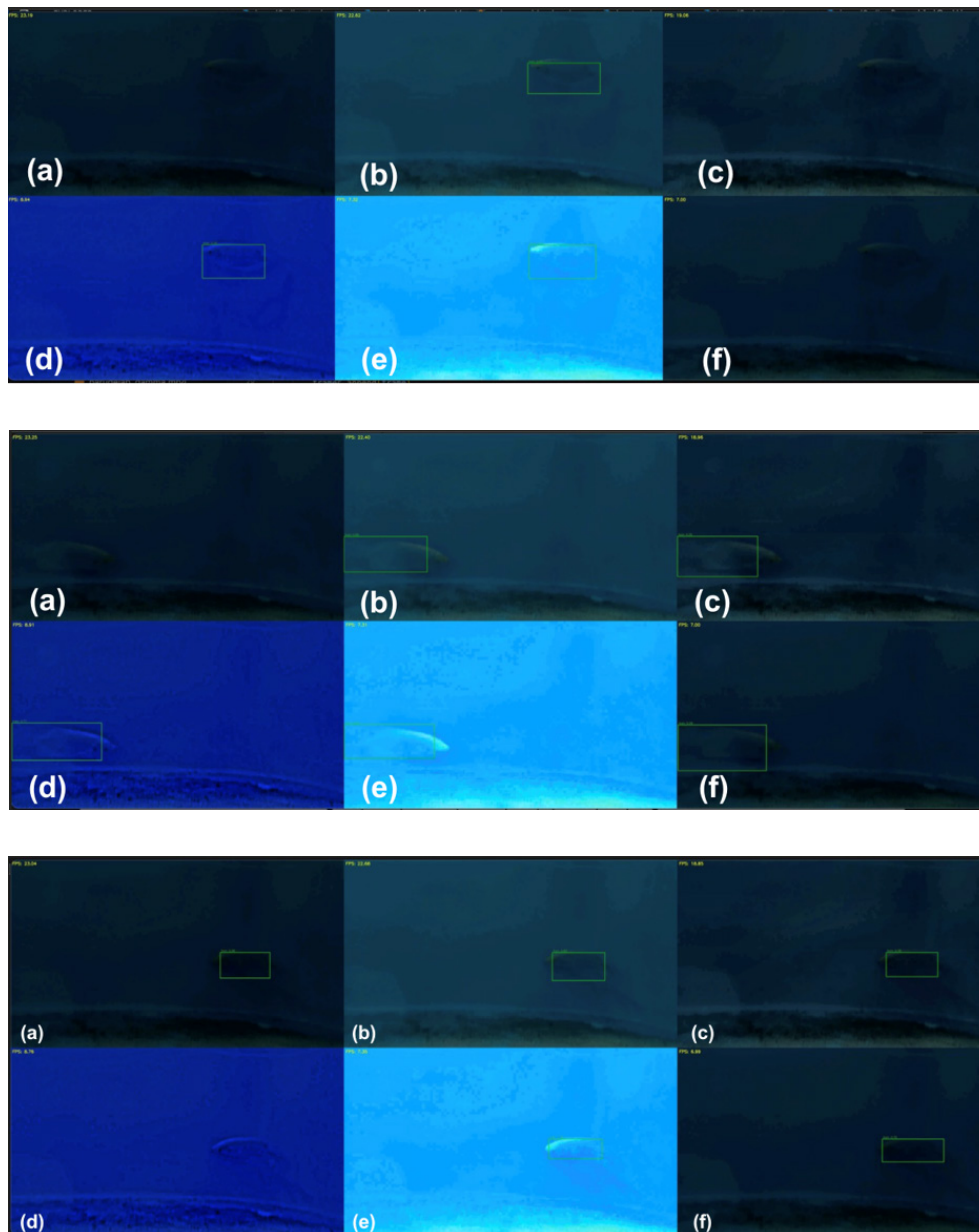


Figure 5. Sample detection results from the video recorded at 16:00 WIB: (a) Original, (b) Gamma and White Balance Correction, (c) CLAHE, (d) Retinex Ultra Lite, (e) UDP, and (f) UDP Super Lite.

These results are consistent with, and extend, prior findings in the underwater image enhancement literature. The strong performance of CLAHE aligns with Garg *et al.* (2018), who reported that CLAHE-based enhancement effectively improves local contrast and detail visibility in underwater images without introducing significant computational overhead. The near-CLAHE accuracy and higher speed obtained with Gamma Correction and White Balance are consistent with Muniraj and Dhandapani (2022), who found that color-constancy correction improves detail preservation while remaining computationally lightweight. The color distortion and lighting-

dependent inconsistency observed for Retinex Ultra Lite echo Tang *et al.* (2019), who noted that Retinex-based enhancement is sensitive to non-uniform illumination and can amplify color artifacts under certain lighting conditions. The high computational cost and low frame rate observed for UDP and UDP Super Lite are consistent with previous reports on dark-channel-prior-based methods, which involve computationally expensive operations such as spatial erosion and transmission-map estimation. Yang *et al.* (2011) and Wu *et al.* (2021) similarly noted that although dark-channel-prior methods can effectively reduce haze, their computational demands make

them less practical for real-time or embedded deployment. Finally, the poor performance of the unenhanced baseline reinforces earlier observations that raw underwater imagery,

degraded by scattering, absorption, and color attenuation, is generally insufficient for reliable object detection without prior enhancement (Schettini and Corchs 2010; Sahu *et al.* 2014).

Table 2. Comparative analysis of image enhancement methods for YOLOv11-based underwater fish detection.

Method	Working Principle	Visual Improvement	Computational Complexity	FPS	Impact on YOLO Detection	Suitable for Real-Time?
No Enhancement	Direct input of raw frames into YOLO	Poor under dark or hazy conditions	None (raw frames; no processing applied)	19–23	Detection fails under low contrast	No (fails under low-light/turbid conditions despite high FPS)
Gamma + White Balance	Brightness correction + color balance adjustment	Natural appearance, though sometimes over-saturated	Very low	19–20	Moderate improvement, especially in dark scenes	Yes
CLAHE	Adaptive histogram equalization on L channel	Significant enhancement of contrast and texture	Moderate	16–19	Improves accuracy in turbid water	Yes
Retinex Ultra Lite	Grayscale/ blurring ratio without log transformation	Moderate contrast, may introduce unnatural colors	Fairly high	8–9	Performance varies depending on water type and color	Less suitable
Underwater Dark Prior (UDP)	Minimum dark channel → transmission estimation	Often over-bright with color distortions	High	5–6	Enhances detection in hazy conditions	Not suitable
UDP Super Lite	Uses channel maximum and simple ratio estimation	Reduces blue/ green haze	Fairly high	7–8	Moderately stable, weak against color noise	Not suitable

Table 3. Performance comparison of six image preprocessing configurations for YOLOv11-based fish detection on a 600-frame test set.

Enhancement Method	Precision	Recall	mAP@0.5	FPS
FPS	0.71	0.68	0.69	21.3
CLAHE	0.86	0.83	0.84	17
Gamma + White Balance	0.84	0.81	0.82	19.8
<i>Retinex Ultra Lite</i>	0.72	0.69	0.70	8.7
<i>UDP Super Lite</i>	0.68	0.65	0.67	7.1
<i>UDP (full)</i>	0.65	0.62	0.64	5.8

CONCLUSION

Combining image enhancement with YOLOv11 improved underwater fish detection under turbidity, blue-green color dominance, and low lighting, confirmed by both qualitative assessment and quantitative evaluation (precision, recall, mAP@0.5) on a 600-frame test set. Among the six scenarios, CLAHE gave the best overall balance (precision 0.86, recall 0.83, mAP@0.5 0.84, 17 FPS) and is selected as the enhancement method for the proposed pipeline. Gamma Correction + White Balance was the strongest alternative (mAP@0.5 0.82, 19.8 FPS) when higher frame rate is prioritized. The unenhanced baseline had the highest FPS (21.3) but the lowest accuracy (mAP@0.5 0.69), while Retinex Ultra Lite, UDP Super Lite, and full UDP all fell below the 15 FPS real-time threshold without exceeding CLAHE's accuracy, making them unsuitable for real-time edge deployment. CLAHE is therefore recommended as the primary enhancement method for real-time embedded underwater vision systems, with Gamma + White Balance as a viable alternative. Future work should extend this evaluation to a larger, multi-species dataset and additional metrics such as F1-score.

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