Fish Disease Detection Using Modified Haar Wavelet with Adaptive Coefficient Selection

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Abstract—**White Spot Disease (WSD) is a major threat to aquaculture production and requires accurate image-based detection methods for early diagnosis. However, disease marker detection in fish images is challenging due to noise, illumination variations, low contrast, and complex background structures. This study proposes a Modified Haar Wavelet framework that integrates adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding for White Spot Disease marker detection. The proposed framework aims to improve edge representation and disease marker localization while preserving disease-related structural information. Performance evaluation was conducted by comparing the proposed method against Otsu, Canny, Adaptive Thresholding, and conventional Haar Wavelet approaches using IoU, Precision, Recall, F1-score, PSNR, and SSIM. The proposed framework achieved the best overall performance with an IoU of 0.819, a precision of 0.849, a recall of 0.799, an F1-score of 0.823, a PSNR of 25.390 dB, and an SSIM of 0.889. Comparative analysis and ablation study further confirmed the effectiveness of adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding. The results demonstrate that the proposed Modified Haar Wavelet framework provides an effective and robust solution for automated detection of White Spot Disease markers in aquaculture images.**

Keywords—Fish disease detection; white spot disease; image analysis; modified Haar wavelet; adaptive coefficient selection; edge detection

I. INTRODUCTION

Fish diseases pose a major threat to aquaculture, reducing productivity, quality, and profitability. Disease outbreaks can reduce annual production by up to 15%, while infections such as Ichthyophthirius, Columnaris, and Epizootic Ulcerative Syndrome (EUS) may cause mortality rates approaching 90% in cultured fish stocks [1], [2]. These losses also threaten food security, particularly in regions that rely heavily on aquaculture as a primary source of protein [3], [4]. Traditional diagnosis based on manual inspection is often subjective and inefficient, highlighting the need for automated detection systems [3]. Recent advances in computer vision and machine learning, including feature ranking techniques and large-scale datasets, have significantly improved recognition accuracy while reducing computational costs [5], [6], [7]. Collectively, these studies demonstrate that automated image analysis offers a promising approach to mitigating the impact of fish diseases and enhancing the sustainability of aquaculture systems [1], [4].

Among the various fish diseases, White Spot Disease (WSD), caused by the protozoan parasite *Ichthyophthirius multifiliis*, is considered one of the most destructive. The disease is characterized by the formation of white cysts on the skin, fins, and gills of infected fish, leading to tissue damage, physiological stress, and mortality rates that can reach 100% if left untreated [8], [9]. Beyond its biological consequences, WSD also imposes a substantial economic burden and threatens the sustainability of the global aquaculture industry [4], [5].

Image processing has become an essential tool across various fields, including medicine, industry, remote sensing, and agriculture. One of the fundamental tasks in image analysis is edge detection, which identifies object boundaries and structural details within an image. Accurate edge detection significantly affects segmentation quality and subsequent classification performance [10], [11], [12]. Classical operators such as Sobel, Prewitt, Roberts, and Canny have been widely employed; however, each method presents certain limitations, particularly when dealing with noise or fine details [13]. To address these challenges, wavelet-based approaches, especially the Haar Wavelet Transform, have attracted considerable attention for their simplicity, computational efficiency, and ability to extract multi-resolution features [14], [15]. Previous studies have shown that the Haar Wavelet improves edge detection accuracy compared to classical operators by providing clearer feature representations [16]. Wavelet-based approaches have also demonstrated strong performance in various medical imaging applications, including skin lesion segmentation, brain tumor classification, mammogram analysis, and breast cancer screening [17], [18], [19]. In these contexts, edge detection plays a central role in extracting boundary and structural information that supports accurate segmentation and classification of diseased regions [10], [11], [20]. These wavelet-based methods have consistently achieved robust performance by extracting multi-resolution features, enhancing edges, and suppressing noise, thereby significantly improving segmentation and classification outcomes. Such success indicates strong potential for adapting wavelet-based techniques to other biological domains, such as aquaculture, where edge detection is equally important for disease identification.

Furthermore, hybrid approaches that integrate wavelet techniques with other computational methods, such as Artificial Neural Networks [21] and texture analysis, have demonstrated improved classification performance and robustness. Studies on image denoising and enhancement using the Discrete Wavelet Transform (DWT) [14], [22], [23], [24], [25] further highlight its adaptability in improving image quality for diagnostic and recognition tasks.

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Despite extensive research in medicine, engineering, and image processing, the application of the Haar Wavelet in aquaculture, particularly for fish disease detection, remains very limited. White Spot Disease (WSD), caused by the protozoan *Ichthyophthirius multifiliis*, is among the most destructive parasitic infections in fish farming, as it manifests through visible white cysts on the skin, fins, and gills, ultimately leading to stress, growth retardation, and mass mortality if not detected at an early stage [9]. Previous studies have demonstrated the effectiveness of Haar and Haar-like wavelet transforms in medical imaging and multi-scale fusion tasks, highlighting their ability to enhance image definition, improve edge representation, and reduce noise interference [22], [23], [24]. Therefore, this study proposes a modified Haar Wavelet integrated with the Roberts operator to optimize edge detection, enhance gradient robustness, and improve the reliability of automated white spot detection in aquaculture images.

The remainder of this study is organized as follows. Section II reviews related work that forms the foundation of the proposed approach. Section III presents a comprehensive description of the proposed methodology. Section IV reports the performance analysis, demonstrating the classification efficiency of the developed system. Finally, Section V concludes the study by summarizing the main findings and key insights.

II. RELATED WORK

The Haar Wavelet has been widely applied in medical imaging to enhance segmentation and classification performance. Several studies have demonstrated its effectiveness in tasks such as skin lesion segmentation, mammogram interpretation, and medical image fusion, where it significantly improves feature extraction and robustness against noise [14], [17], [23]. In brain tumor segmentation, [18] conducted a comparative analysis of several techniques, including Haar DWT, Otsu, Watershed, and CNN methods. He found that although CNN achieved the highest accuracy, Haar DWT remained a valuable approach for multi-scale feature extraction in biomedical images. Collectively, these findings confirm the adaptability of Haar-based techniques in handling fine details within diagnostic applications.

Beyond the medical domain, several studies have compared the Haar Wavelet with classical edge detection operators such as Sobel, Prewitt, Roberts, Laplacian, and Canny. Although these traditional methods are widely used, they often suffer from noise sensitivity and detail loss, particularly in high-frequency regions [10], [18]. In contrast, wavelet-based methods, especially the Haar Wavelet, consistently provide clearer edge representations and superior noise reduction capabilities [14], [25]. This balance between precision and robustness makes the Haar Wavelet a preferred approach when classical operators exhibit performance limitations.

The Haar Wavelet has also been modified and adapted for various applications beyond medical imaging. Quantum-inspired approaches have been developed for edge detection and image watermarking, achieving improved detail preservation and enhanced PSNR robustness [16], [26]. In classification tasks, entropy-based formulations have been introduced to improve the efficiency and reliability of Haar features [27]. In contrast, in remote sensing, wavelet-based feature enhancement modules have significantly improved semantic segmentation performance when integrated with CNN and transformer architectures [24]. Other studies have focused on optimizing Haar Wavelet methods for resource efficiency, such as energy-efficient signal processing architectures for biomedical data [28]. Collectively, these studies demonstrate the flexibility of the Haar Wavelet, which can be adapted to a wide range of objectives, from optimizing classification to integrating with deep learning frameworks.

Nevertheless, several limitations of the standard Haar Wavelet have also been reported. Research [29] found that although Haar DWT achieves high compression performance, it is less effective for highly detailed images, indicating its weakness in handling fine textures. Although Haar Wavelet has demonstrated effectiveness for edge detection and noise suppression [14], the direct use of wavelet detail coefficients may result in the loss of fine structural information and incomplete edge representation in complex imaging environments. Other studies have further revealed that the Haar Wavelet suffers from noise sensitivity, discontinuous edge representation, and limited capability in modeling complex textures [23], [25], [27]. These limitations highlight the need to modify the Haar Wavelet to improve gradient robustness, edge continuity, and segmentation accuracy.

Although the Haar Wavelet has demonstrated strong adaptability across various domains, its application in aquaculture remains very limited. Research on fish disease detection has generally focused on traditional image enhancement techniques and machine learning methods, with only a few studies exploring wavelet-based approaches. Studies on the use or modification of the Haar Wavelet for White Spot Disease (WSD) detection remain infrequent, leaving considerable opportunities for further investigation. This condition highlights the urgency of developing a Modified Haar Wavelet approach specifically designed for aquaculture image analysis, intending to improve edge representation and enhance the reliability of automated disease detection [16], [24], [26].

Edge detection has long been recognized as a fundamental stage in image analysis because it defines object boundaries and structural details that directly affect segmentation accuracy. Classical edge detection operators, including Sobel, Prewitt, Roberts, Laplacian, and Canny, are widely adopted due to their simplicity and computational efficiency. However, previous studies have reported that these methods often suffer from noise sensitivity, edge discontinuity, and the inability to preserve fine details, particularly in textured or low-quality images [30]. To overcome these limitations, several adaptive and intelligent approaches have been introduced. Histogram-based preprocessing techniques have been shown to improve the performance of the Canny operator in noisy environments, thereby enhancing edge detection accuracy. In addition, fuzzy logic–based methods provide more flexible edge extraction by incorporating linguistic rules. In retinal blood vessel detection, Type-2 fuzzy systems demonstrated greater adaptability to variations in image quality than fixed-threshold approaches [31].

Recent developments have shown that wavelet-based approaches provide significant improvements in edge detection performance through multi-resolution analysis. Research [14] demonstrated that the Haar Wavelet produces clearer, more stable edges than classical operators and provides superior denoising capability. Similarly, [25] confirmed that wavelet-domain denoising improves the signal-to-noise ratio and preserves edge clarity more effectively than conventional filtering techniques. More advanced developments include quantum-inspired Haar variants that improve detail preservation, although they require relatively high computational resources [26]. Research [24] further demonstrated that wavelet-based feature enhancement significantly improves semantic segmentation performance by preserving high-frequency edge information that is commonly lost in deep learning models.

Wavelet Transform (WT) has therefore become one of the most widely used approaches in image processing because of its capability to extract information at multiple resolutions and scales. Compared with conventional edge detection operators such as Sobel, Prewitt, and Canny, WT provides greater robustness and adaptability in handling noise and fine image details. Consequently, WT has been extensively applied in segmentation, edge detection, denoising, image enhancement, and image compression tasks [32], [33].

Among wavelet techniques, the Haar Wavelet remains highly relevant for its computational efficiency and mathematical simplicity. Previous studies have reported that Haar Wavelet–based approaches achieve more accurate results than classical edge detection techniques [14]. Younus and Hasan [15] applied the Haar Wavelet for Deepfake detection and achieved an accuracy exceeding 90%, confirming its effectiveness in identifying edge inconsistencies caused by digital manipulation. In image compression applications, Kanagaraj and Muneeswaran [29] highlighted the Haar Wavelet's ability to achieve high compression ratios without significant degradation in image quality.

The effectiveness of WT has also been widely demonstrated in medical imaging applications. Research [33] applied DWT with thresholding to X-ray images, successfully improving PSNR and SNR. Research [32] combined WT with a backpropagation neural network for bone fracture detection, achieving highly accurate classification performance. Furthermore, [28] proposed an energy-efficient Haar-5 architecture for respiratory signal processing, reducing power consumption by more than 38% compared with conventional architectures, making it highly suitable for Internet of Things (IoT)-based medical applications.

Beyond medical imaging, WT has shown strong performance across various application domains. research [34] integrated WT with recursive operators for road identification in remote sensing images, obtaining segmentation results that were more robust to noise. Research [35] utilized DWT to optimize brain tumor detection, further highlighting the adaptability of wavelet-based techniques in medical diagnostics. More recently, [26] introduced a quantum-based modification of the Haar Wavelet that improved edge representation accuracy in medical images, representing a significant advancement in wavelet-based methodologies.

Despite the promising performance of wavelet-based approaches, several limitations remain. Classical Haar Wavelet methods still struggle to preserve fine-edge continuity and to handle complex textures under noisy conditions [14], [25]. In addition, some advanced Haar-based modifications are computationally expensive, limiting their applicability to large-scale or real-time systems [26]. Furthermore, although wavelet-based methods have been extensively explored in medical imaging, remote sensing, image compression, and Deepfake detection, their application in aquaculture image analysis, particularly for White Spot Disease detection in fish, remains very limited. This gap highlights the need for a modified Haar Wavelet framework to improve edge representation and enhance the reliability of automated disease detection in aquaculture images.

To address this gap, this study proposes a Modified Haar Wavelet framework that integrates adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding within a unified processing pipeline. Unlike conventional Haar Wavelet approaches that directly use wavelet detail coefficients, the proposed framework adaptively processes these coefficients before gradient extraction, thereby improving disease marker localization while suppressing irrelevant image structures. The main scientific contribution of this work lies in integrating adaptive coefficient processing and edge-refinement strategies for White Spot Disease marker detection. Furthermore, the proposed framework extends the conventional Haar Wavelet approach by incorporating adaptive coefficient selection and edge-refinement mechanisms, and its effectiveness is validated through comparative benchmarking and ablation studies.

Specifically, the proposed framework modifies the conventional Haar Wavelet by integrating it with the Roberts Operator to enhance edge detection performance. The Haar Wavelet enables multi-resolution decomposition but often loses fine edge details [14], [36]. To address this limitation, the Roberts Operator is applied to the Haar detail coefficients, thereby improving gradient localization and producing clearer edges or external markers for segmentation. This modification is expected to provide more accurate detection of white spot disease in fish.

III. RESEARCH METHODOLOGY

This section presents the research methodology used to develop the proposed White Spot Disease detection framework. The methodology covers the overall research workflow, image preprocessing, Haar Wavelet decomposition, and the proposed modification, which integrates the Roberts operator for edge enhancement.

A. Dataset Acquisition

The fish specimens used in this study were obtained from the National Fish Health Research Center (NaFish) at the Fisheries Research Institute (FRI), Batu Maung, Penang, Malaysia. Sea bass (Lates calcarifer), a major aquaculture species in Malaysia and highly susceptible to White Spot Disease (WSD), was selected as the experimental species.

Underwater videos were recorded under controlled aquarium conditions using a GoPro Hero 9+ camera at a resolution of 4K (3840 × 2160 pixels) and 60 frames per second. To ensure consistency during data acquisition, the aquarium environment was maintained under stable lighting and background conditions throughout the recording process. The recorded videos were subsequently processed to extract image frames for experimental analysis.

A total of 4,137 image frames were extracted from the recorded videos, comprising 2,845 images of infected fish exhibiting visible White Spot Disease (WSD) symptoms and 1,292 images of healthy fish. These images were used as the experimental dataset for evaluating the proposed Modified Haar Wavelet framework. The extracted images served as input for preprocessing, wavelet decomposition, edge detection, and quantitative performance evaluation. The performance of the proposed method was evaluated against expert-annotated ground truth masks.

- The fish images used in this study were obtained from NaFish and FRI, where the specimens had been previously identified as exhibiting White Spot Disease (WSD) symptoms. Ground-truth masks were generated using the LabelMe annotation tool by manually marking visible white-spot regions in the infected fish images. The annotation process focused on identifying white, cyst-like spots on the fish's body and fins. The resulting binary masks were used as reference annotations for quantitative evaluation.
- The collected images exhibit common underwater imaging challenges, including uneven illumination, water reflections, suspended particles, low contrast, and variations in fish orientation. These characteristics were preserved to ensure that the proposed method was evaluated under realistic aquaculture monitoring conditions. The extracted image frames were subsequently used as input for the preprocessing, wavelet decomposition, and edge detection stages of the proposed Modified Haar Wavelet framework.

B. Research Framework

This study proposes a Modified Haar Wavelet–based framework, integrated with the Roberts operator, for automatic detection of White Spot Disease (WSD) in fish images. The proposed framework is designed to improve edge representation and enhance the reliability of disease identification under challenging aquaculture imaging conditions, such as noise, uneven illumination, and low contrast. Overall, the system consists of several sequential stages: image acquisition and preprocessing, wavelet-based edge enhancement and gradient extraction, and edge map generation for disease detection.

In the initial stage, the input fish image undergoes enhancement to improve visual quality and reduce noise. After preprocessing, the enhanced image is decomposed using the Haar Wavelet Transform for multi-resolution analysis. The decomposition process separates the image into approximation and detail coefficients, enabling more effective extraction of high-frequency information associated with object boundaries and white-spot patterns. To improve edge representation, adaptive coefficient thresholding is applied to the Haar detail coefficients, suppressing noise while preserving significant edge structures.

The proposed modification is achieved by integrating the Roberts operator with the adaptively processed Haar detail coefficients. Unlike conventional edge detection approaches that apply gradient operators directly to the original image, the proposed framework applies the Roberts operator to the Haar detail coefficients before image reconstruction. This strategy improves gradient localization and enhances fine edge structures associated with White Spot Disease markers. The overall workflow of the proposed framework is illustrated in Fig. 1.

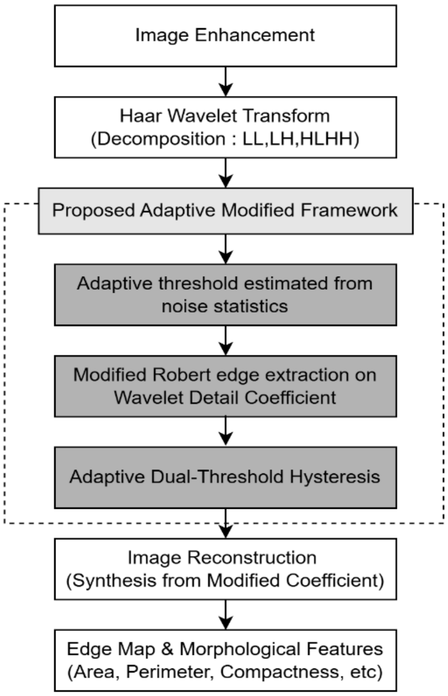

Fig. 1. Flowchart of the proposed method.

The adaptive threshold applied to the detail coefficients is calculated using:

$$T = \sigma\sqrt{2\log(N)}\ x\ \alpha \tag{1}$$

where, T represents the adaptive threshold, σ denotes the estimated noise level, $N$is the total number of image pixels, and $\alpha$is the threshold scaling parameter.

After adaptive coefficient processing, the Haar detail coefficients are further processed with the Roberts operator to improve gradient localization along high-frequency edge structures. The gradient magnitude is then computed using:

$$M(x,y) = \sqrt{{G_x}^2 + {G_y}^2} \tag{2}$$

where, $G_x$and $G_y$denote the horizontal and vertical gradients, respectively.

To generate a more stable and continuous edge map, hysteresis thresholding is applied to the gradient map using dualthreshold processing. The high threshold is determined by using:

$$T_{high} = Percentile\ (G, 90) \tag{3}$$

while the low threshold is computed as:

$$T_{low} = T_{high}\ x\ 0.40 \tag{4}$$

This process preserves weak edges connected to strong edges, thereby improving edge continuity and reducing fragmented edge structures caused by noise and uneven illumination. As a result, the proposed framework can generate clearer, more stable edge representations for White Spot Disease detection in aquaculture images.

Overall, the proposed Modified Haar Wavelet framework integrates adaptive coefficient processing, Roberts-based gradient extraction, and hysteresis thresholding to improve edge representation for detecting White Spot Disease in fish images. Unlike conventional Haar Wavelet approaches that either directly use the detail coefficients or apply gradient operators to the original image, the proposed framework performs adaptive processing on the Haar detail coefficients before gradient extraction. This strategy enables the framework to suppress noise while preserving important high-frequency edge structures associated with White Spot Disease patterns.

Haar Wavelet was selected because it preserves high-frequency image information and edge structures while maintaining low computational complexity [24], [26]. Adaptive coefficient selection was introduced to retain significant wavelet coefficients associated with disease markers while reducing noise and irrelevant textures [24]. Roberts operator was employed for its ability to enhance fine-edge details and subtle structural information that may correspond to White Spot Disease markers [19]. Finally, hysteresis thresholding was applied to improve edge continuity and reduce fragmented detections during the final marker extraction stage. The integration of adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding enables more accurate localization of disease markers while preserving important structural information in fish images.

The proposed framework was designed to evaluate the contributions of adaptive coefficient selection systematically, Roberts operator-based edge enhancement, and hysteresis thresholding for White Spot Disease marker detection. The experimental design includes quantitative evaluation using multiple performance metrics and comparative analysis against conventional methods to ensure a comprehensive assessment of the proposed approach.

IV. RESULTS AND ANALYSIS

This section presents the experimental evaluation of the proposed White Spot Disease marker detection framework based on the Modified Haar Wavelet with Adaptive Coefficient Selection. The performance evaluation was conducted on the complete dataset described in Section III, comprising 4,137 image frames: 2,845 infected fish images and 1,292 healthy fish images. The reported results represent the overall performance of each method on the evaluation dataset and were analyzed through quantitative and qualitative comparisons.


(a) (b)

Fig. 2. Image enhancement result: (a) Original image, (b) Image enhancement.

Fig. 2 shows the result of the image enhancement process applied to the original fish image. The enhancement stage improves image contrast and emphasizes important surface features associated with fish disease patterns. In addition, the enhancement process increases edge visibility and texture clarity, making the infected regions more distinguishable from the background. Noise and low-intensity regions are also reduced through adaptive coefficient selection in the Modified Haar Wavelet transform. As a result, the enhanced image yields sharper object boundaries and more stable structural information, thereby supporting more accurate detection and feature extraction in the subsequent processing stage.

After image enhancement, the visual quality of the fish images improved, with higher contrast that highlights surface features and yields clearer, more stable contours than traditional methods. One of the main modifications was made during the coefficient-selection stage of the Haar Wavelet transform. In the conventional method, these coefficients are typically processed directly without further selection. In this study, however, an adaptive coefficient selection method is used to select coefficients based on specific criteria, such as intensity or spatial distribution patterns. This approach allows the processing to focus more on relevant features while ignoring less important elements or those that may introduce noise. In addition, another modification is to incorporate the Roberts Operator into the selected Haar Wavelet coefficients. The Roberts Operator is employed to quickly and effectively detect edges in the wavelet domain and enhance disease-related edge structures. The next step in the modification is to calculate the gradient magnitude directly from the coefficients obtained by applying the Roberts Operator to the image. The resulting gradient values are then further refined by thresholding to produce a gradient map. This technique helps separate important regions from the background, allowing key features to be highlighted more clearly.

Fig. 3 presents the visual comparison of White Spot Disease marker detection results obtained using Adaptive Thresholding, Canny, Otsu, conventional Haar Wavelet, and the proposed Modified Haar Wavelet framework. Significant differences can be observed among the methods in terms of marker localization accuracy and noise suppression.

Adaptive Thresholding [Fig. 3(a)] detects numerous small regions but also produces scattered responses due to image noise and illumination variations. Canny edge detection [Fig. 3(b)] produces thin edge responses; however, only a limited number of disease markers are successfully detected. Otsu thresholding [Fig. 3(c)] generates large, segmented regions that include substantial portions of the fish body, indicating over-detection and poor discrimination between disease markers and background structures. Conventional Haar Wavelet [Fig. 3(d)] reduces some background interference but fails to preserve several disease markers, resulting in incomplete detection.

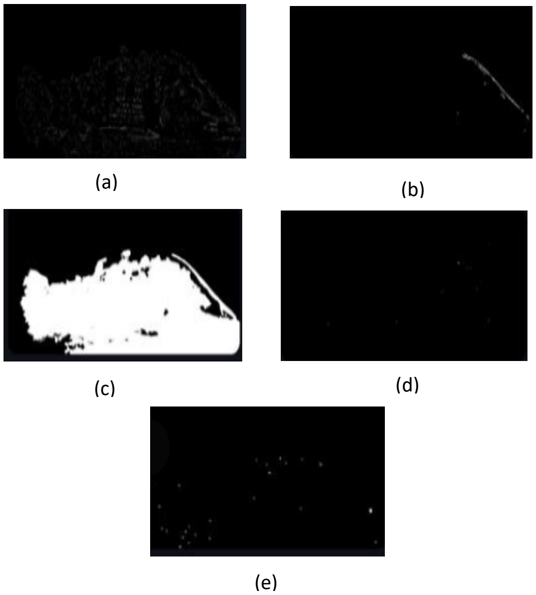

Fig. 3. Comparison results of edge detection methods: (a) Adaptive, (b) Canny, (c) Otsu, (d) Haar wavelet, and (e) Proposed modified Haar wavelet method.

In contrast, the proposed Modified Haar Wavelet framework [Fig. 3(e)] yields more localized and distinct disease-marker responses while effectively suppressing irrelevant background information. The detected marker distribution more closely matches the expected disease locations, demonstrating improved edge representation and marker-extraction capability. These visual observations are consistent with the quantitative results presented in Table I, where the proposed method achieves the highest IoU, Precision, F1-score, PSNR, and SSIM values among all evaluated methods.

TABLE I. COMPARISON OF EDGE DETECTION METHODS BASED ON EVALUATION METRICS

Method	Otsu	Canny	Adaptive	Haar Wavelet	Proposed
Iou	0.450	0.380	0.520	0.350	0.819
Precision	0.520	0.610	0.580	0.480	0.849
Recall	0.680	0.420	0.710	0.550	0.799
F1Score	0.590	0.500	0.640	0.510	0.823
PSNR	18.5	20.1	19.8	19.2	25.390
SSIM	0.720	0.750	0.780	0.730	0.889

Based on Table I, the proposed Modified Haar Wavelet framework achieved the best overall detection performance compared to the conventional methods. The integration of adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding significantly improved the accuracy of disease marker localization and structural preservation in White Spot Disease images.

The proposed method achieved the highest IoU value of 0.819, outperforming Adaptive Thresholding (0.520), Otsu (0.450), Canny (0.380), and conventional Haar Wavelet (0.350). A higher IoU value indicates a greater overlap between the detected marker regions and the corresponding ground-truth annotations. This result demonstrates that the proposed framework provides more accurate localization of disease markers while reducing background misclassification.

In terms of precision, the proposed method achieved the highest value of 0.849, indicating that the detected marker regions contain fewer false-positive responses than competing methods. The precision values of Otsu, Canny, Adaptive Thresholding, and conventional Haar Wavelet were 0.520, 0.610, 0.580, and 0.480, respectively. This improvement suggests that the proposed framework effectively suppresses irrelevant image structures while preserving disease-related features.

Although the proposed method did not achieve the highest recall, it maintained a high recall of 0.799, which is higher than those of Otsu (0.680), Adaptive Thresholding (0.710), Canny (0.420), and conventional Haar Wavelet (0.550). The combination of high precision and high recall yielded the highest F1-score of 0.823, indicating balanced and reliable detection performance.

The image quality evaluation further supports the effectiveness of the proposed framework. The proposed method achieved the highest PSNR value of 25.390 dB, exceeding Otsu (18.5 dB), Canny (20.1 dB), Adaptive Thresholding (19.8 dB), and conventional Haar Wavelet (19.2 dB). This result indicates better preservation of relevant image information and reduced distortion during detection.

Similarly, the proposed framework obtained the highest SSIM value of 0.889, demonstrating superior structural similarity between the detected marker regions and the reference annotations. In comparison, the SSIM values of Otsu, Canny, Adaptive Thresholding, and conventional Haar Wavelet were 0.720, 0.750, 0.780, and 0.730, respectively. The higher SSIM value confirms that the proposed method more effectively preserves disease marker structures and image characteristics.

Although PSNR and SSIM indicate that the proposed framework effectively preserves image quality and structural information, these metrics are not the primary objective of the study. The main focus of the proposed framework is accurate localization of disease markers. Therefore, IoU, Precision, Recall, and F1-score provide more direct evidence of detection performance than image quality metrics alone.

Overall, the results demonstrate that the proposed Modified Haar Wavelet framework consistently outperforms conventional edge detection methods across all evaluation metrics. The combination of adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding significantly improves disease marker localization accuracy, structural preservation, and overall detection reliability for White Spot Disease images.

Recent deep learning approaches, particularly convolutional neural networks (CNNs), have demonstrated strong performance in fish disease detection tasks [37]. Furthermore, integrating edge-based feature extraction with deep learning models has shown promising results in medical image analysis and disease screening applications [19]. Wavelet-based feature enhancement techniques have also been successfully employed to improve detection accuracy and preserve structural information in complex imaging environments [24]. In addition, recent quantum-inspired Haar Wavelet approaches have demonstrated improved edge preservation and detail representation for image edge detection tasks [26]. While deep learning-based methods often require large, annotated datasets and extensive training procedures, wavelet-based approaches provide a robust alternative for feature extraction and edge analysis. In this context, the proposed Modified Haar Wavelet framework provides a lightweight solution while maintaining effective edge representation and disease marker extraction capability.

To address the growing development of deep learning and wavelet-based techniques in disease detection and image analysis, Table II presents a comparison of recent approaches and highlights the position of the proposed Modified Haar Wavelet framework relative to existing methods.

TABLE II. POSITIONING OF THE PROPOSED FRAMEWORK AGAINST RECENT STUDIES

Study	**Method**	**Category**	**Main Contribution**
Harun et al. [37]	CNN	Deep learning	Fish disease detection
Dey et al. [19]	Edge detection + deep transfer learning	Deep learning	Disease screening
Li et al. [24]	Wavelet feature enhancement	Wavelet-based	Semantic segmentation improvement
Wang et al. [26]	Quantum Haar Wavelet	Wavelet-based	Edge preservation and edge detection
Proposed	Modified Haar Wavelet	Wavelet-based	White spot disease marker detection

Table II positions the proposed method relative to recent deep learning-based and wavelet-based approaches reported in the literature. Deep learning methods, such as CNNs and deep transfer learning, have demonstrated strong performance in disease detection and screening tasks. Meanwhile, wavelet-based approaches have been successfully employed for semantic segmentation, edge preservation, and image feature enhancement. In contrast to deep learning methods, the proposed Modified Haar Wavelet framework does not require model training or large annotated datasets. Compared with existing wavelet-based approaches, the proposed framework introduces adaptive coefficient selection, integration of the Roberts operator, and hysteresis thresholding to improve white spot marker localization and edge representation.

To further validate the effectiveness of the proposed modifications, a comparative analysis was performed between the conventional Haar Wavelet and the proposed Modified Haar Wavelet framework. This comparison aims to evaluate the overall contribution of adaptive coefficient selection, Roberts operator integration, and hysteresis thresholding to disease marker localization and structural preservation. The results are summarized in Table III.

TABLE III. PERFORMANCE COMPARISON OF CONVENTIONAL AND MODIFIED HAAR WAVELET FRAMEWORKS

Method	**IoU**	**Prec.**	**Rec.**	**F1 Score**	**PSNR**	**SSIM**
Haar Wavelet	0.350	0.480	0.550	0.510	19.2	0.730
Proposed	0.819	0.849	0.799	0.823	25.390	0.889

As shown in Table III, the proposed Modified Haar Wavelet framework consistently outperformed the conventional Haar Wavelet across all evaluation metrics. The IoU increased substantially from 0.350 to 0.819, indicating a significantly higher overlap between the detected White Spot Disease (WSD) markers and the corresponding ground-truth annotations. Similarly, Precision improved from 0.480 to 0.849, demonstrating the effectiveness of the proposed framework in reducing false-positive detections.

The Recall value also increased from 0.550 to 0.799, indicating that a larger proportion of disease markers were successfully detected. As a result, the F1-score improved considerably from 0.510 to 0.823, confirming a better balance between Precision and Recall. These improvements suggest that integrating adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding improves disease marker localization performance compared to the conventional Haar Wavelet approach.

Furthermore, the proposed framework achieved a higher PSNR of 25.390 dB, compared to 19.2 dB with the conventional Haar Wavelet. This result indicates improved preservation of relevant image information while reducing unwanted distortions during detection. Likewise, the SSIM value increased from 0.730 to 0.889, demonstrating superior structural similarity and better preservation of disease-related image characteristics.

Overall, the comparative analysis confirms that the proposed modifications significantly improve the performance of the conventional Haar Wavelet framework. The results demonstrate that integrating adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding improves disease marker detection accuracy, structural preservation, and overall detection reliability.

While the comparative analysis demonstrates that the proposed Modified Haar Wavelet framework significantly outperforms the conventional Haar Wavelet approach, it does not reveal the individual contribution of each component within the proposed framework. Therefore, an ablation study was conducted to systematically evaluate the impact of adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding on overall detection performance. By removing one component at a time while preserving the remaining processing stages, the contribution of each component can be quantitatively assessed. The results of the ablation study are presented in Table IV.

Table IV presents the ablation study results of the proposed Modified Haar Wavelet framework. The objective of this analysis is to evaluate the contributions of adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding to the overall performance of White Spot Disease marker detection.

TABLE IV. ABLATION STUDY OF THE PROPOSED MODIFIED HAAR WAVELET FRAMEWORK

Configuration	IoU	Prec.	Rec.	F1 Score	PSNR	SSIM
Without Adaptive Coefficient Selection	0.614	0.827	0.599	0.695	19.040	0.844
Without Roberts Operator	0.671	0.833	0.655	0.733	20.818	0.856
Without Hysteresis Thresholding	0.573	0.823	0.559	0.665	17.770	0.835
Proposed	0.819	0.849	0.799	0.823	25.390	0.889

The complete framework achieved the highest performance across all evaluation metrics, obtaining an IoU of 0.819, a precision of 0.849, a recall of 0.799, an F1-score of 0.823, a PSNR of 25.390 dB, and an SSIM of 0.889. These results indicate that integrating all proposed components effectively improves disease marker localization while preserving structural information.

When adaptive coefficient selection was removed, the IoU decreased from 0.819 to 0.614, and the F1-score decreased from 0.823 to 0.695. This reduction demonstrates that adaptive coefficient selection plays an important role in preserving significant wavelet coefficients associated with disease markers while suppressing irrelevant image structures and noise.

Similarly, removing the Roberts operator reduced the IoU to 0.671 and the F1-score to 0.733. The decrease in performance indicates that Roberts operator-based edge enhancement contributes to improved gradient localization and more accurate representation of disease marker boundaries.

The largest performance degradation occurred when hysteresis thresholding was removed. In this configuration, the IoU dropped to 0.573, the F1-score decreased to 0.665, and PSNR and SSIM were reduced to 17.770 dB and 0.835, respectively. These results suggest that hysteresis thresholding plays a critical role in maintaining edge continuity, reducing fragmented detections, and preserving the connectivity of disease marker structures. By linking weak edge responses to neighboring strong edges, hysteresis thresholding enables more complete and coherent localization of disease markers, thereby significantly improving the overall detection performance of the proposed framework.

Overall, the ablation study confirms that each component contributes positively to the final performance of the proposed framework. The superior results achieved by the complete framework demonstrate that the performance improvement is not due to a single processing stage but to the synergistic integration of adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding.

To provide a holistic view of detection performance, Fig. 4 presents a visual comparison of all evaluated methods across IoU, Precision, Recall, F1-score, PSNR, and SSIM. This visualization complements the quantitative results by illustrating each method's performance trends and highlighting the consistent superiority of the proposed Modified Haar Wavelet framework across multiple evaluation criteria.

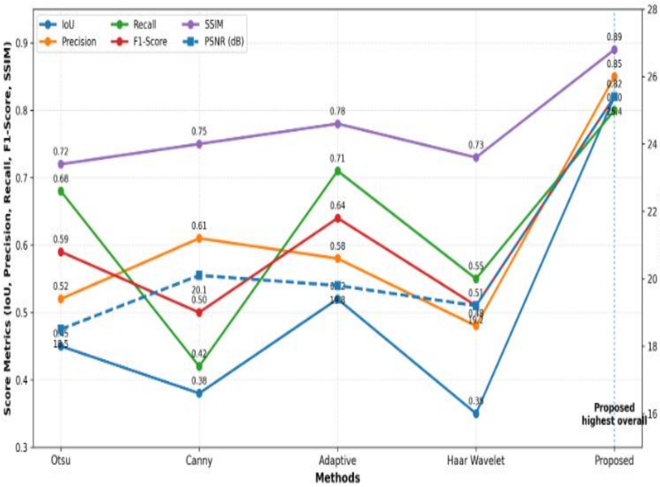

Fig. 4. Overall performance comparison of Otsu, Canny, Adaptive Thresholding, conventional Haar Wavelet, and the proposed Modified Haar Wavelet Framework, evaluated using IoU, Precision, Recall, F1-score, PSNR, and SSIM.

Fig. 4 presents a comprehensive comparison of the evaluated methods across six performance metrics, namely IoU, Precision, Recall, F1-score, PSNR, and SSIM. The graph clearly illustrates the performance trends of each method and highlights the effectiveness of the proposed Modified Haar Wavelet framework.

The proposed method consistently achieved the highest values across all evaluation metrics. In terms of localization accuracy, the proposed framework obtained the highest IoU value of 0.819, indicating superior overlap between the detected White Spot Disease markers and the corresponding ground-truth annotations. Similarly, the highest Precision value of 0.849 demonstrates the framework's ability to minimize false-positive detections while accurately identifying disease markers.

The Recall value of 0.799 indicates that the proposed framework successfully detected most disease markers present in the image. The combination of high Precision and Recall yielded the highest F1-score of 0.823, confirming balanced and reliable detection performance. In contrast, conventional methods such as Otsu, Canny, Adaptive Thresholding, and Haar Wavelet exhibited lower and less consistent performance across these metrics.

The graph also demonstrates the proposed framework's superiority in preserving image quality. The PSNR value reached 25.390 dB, significantly exceeding the values obtained by the conventional methods, which ranged from 18.5 dB to 20.1 dB. Likewise, the proposed framework achieved the highest SSIM value of 0.889, indicating better preservation of structural information and disease-related image characteristics.

Fig. 4 visually confirms the quantitative findings presented in Table I. The consistent dominance of the proposed framework across all evaluation metrics demonstrates that integrating adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding effectively improves disease marker localization, edge representation, and structural preservation in White Spot Disease detection.

The experimental results further indicate that the proposed Modified Haar Wavelet framework consistently outperforms conventional edge detection methods across all evaluation metrics. The combination of adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding significantly improves disease marker localization accuracy, structural preservation, and overall detection reliability for White Spot Disease images.

These findings suggest that the proposed framework effectively prioritizes disease marker localization while preserving important structural information. Although the method achieves superior detection performance, further investigation is required to evaluate computational efficiency, scalability, and real-time applicability in large-scale aquaculture monitoring systems.

V. CONCLUSION

This study proposed a Modified Haar Wavelet framework for White Spot Disease marker detection by integrating adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding. The proposed framework was designed to improve disease marker localization and edge representation while preserving important structural information in fish images.

Experimental results demonstrated that the proposed framework consistently outperformed Otsu, Canny, Adaptive Thresholding, and conventional Haar Wavelet methods across all evaluation metrics. The proposed method achieved the highest IoU (0.819), Precision (0.849), Recall (0.799), F1-score (0.823), PSNR (25.390 dB), and SSIM (0.889), indicating superior detection accuracy and structural preservation. Comparative analysis further confirmed that the proposed modifications significantly improved the performance of the conventional Haar Wavelet framework.

The ablation study verified the contribution of adaptive coefficient selection, Roberts operator-based edge enhancement, and hysteresis thresholding, demonstrating that the performance improvement resulted from the synergistic integration of all components rather than a single processing stage. These findings highlight the effectiveness of the proposed framework as a robust wavelet-based solution for automated detection of White Spot Disease markers.

Future work will focus on evaluating robustness under more diverse aquaculture conditions, analyzing computational efficiency, and integrating learning-based approaches to further improve detection performance and real-time applicability.

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