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Fish Species Detection Using Deep Learning

Prasanna Mehata[1], Raghavendra Ghodse[2], Rahul Dodamani[3], Samata Maddani[4], Prof. Raghavendra Nagaralli[5]

1,2,3,4 Students of Dept of ECE, KLS VDIT, Haliyal

5, Assistant Professor of Dept of ECE, KLS VDIT, Haliyal

Abstract: Underwater image degradation caused by light absorption, scattering, color loss, and turbidity significantly reduces the accuracy of aquatic vision systems. This paper proposes an integrated framework for underwater fish species detection that combines advanced image enhancement with a lightweight deep-learning classifier. The enhancement stage utilizes a diffusion-based restoration model to recover color fidelity, suppress noise, and improve global image contrast. The enhanced images are subsequently processed by a MobileNetV2-based classification network, optimized for real-time deployment on resource-limited devices. Experimental evaluation using UIQM, UCIQE, PSNR, SSIM, and accuracy demonstrates remarkable improvement in visual quality and species recognition performance. The proposed system offers a robust, scalable solution suitable for aquaculture monitoring, marine biodiversity documentation, and underwater robotics.

Keywords: Underwater Image Enhancement, Diffusion Model, MobileNetV2, Fish Species Detection, Deep Learning.

I. INTRODUCTION

. Underwater visual monitoring systems are essential in marine biology, aquaculture, and ecological conservation. However, the underwater environment inherently introduces challenges such as color attenuation, low contrast, haze, and non-uniform illumination. These issues degrade feature quality and obstruct the performance of automated fish species recognition systems. Recent progress in deep learning has significantly enhanced object detection and classification, but their performance still heavily depends on image clarity. Traditional enhancement approaches such as histogram equalization or white-balancing techniques fail to generalize across varying water conditions. To address this gap, modern diffusion-based image restoration models offer superior reconstruction capability by iteratively denoising and enhancing images in a probabilistic manner. This work presents a unified pipeline that enhances images captured underwater and detects fish species using an optimized convolutional architecture. The combination of diffusion-based enhancement with MobileNetV2 enables both high accuracy and low computational cost, making the system suitable for real-time underwater operations

II. LITERATURE SURVEY

Recent progress in underwater image restoration has increasingly shifted from traditional CNN and GAN architectures towards diffusion-based generative models. Ding et al. (2025) introduced an adversarial diffusion framework for underwater enhancement, demonstrating significant improvements in color fidelity and edge preservation compared to conventional GAN-based enhancers. Their findings show how diffusion models outperform earlier adversarial networks especially under conditions of high turbidity and color degradation, where GANs commonly fail to maintain structural details

Similarly, Zhang (2024) proposed a probabilistic diffusion model that incorporates underwater degradation priors to adaptively restore images across varying water depths. The method achieved higher UIQM and UCIQE scores compared to most 2022–2023 GAN and CNN models, further validating the dominance of diffusion-driven reconstruction. In a parallel direction, Fang et al. (2025) introduced a multiscale diffusion restoration pipeline capable of handling strong scattering effects, reporting significant gains in PSNR and SSIM across multiple benchmark datasets.

For underwater fish species recognition, recent studies emphasize the significance of integrating enhancement with classification. Siri et al. (2024) showed that combining pre-processing using an optimized enhancement network with lightweight CNN classifiers drastically improves recognition accuracy for small and visually similar species. In particular, MobileNet-based classifiers continue to be favored for real-time applications due to their low computational cost. Several 2024–2025 papers have demonstrated that MobileNetV2 and its enhanced variants outperform deeper networks like ResNet when deployed on mobile or embedded underwater systems.

More recent literature also emphasizes task-aware enhancement where the enhancement model is trained with downstream detection objectives in mind. Studies from 2024 and early 2025 report that direct application of enhancement models can sometimes introduce distribution shifts harmful to classification. Therefore, many newer pipelines jointly optimize enhancement and recognition models or use detection-guided enhancement to ensure semantic consistency.

III. RESEARCH METHODOLGY

Dataset Collection: Underwater fish images were collected from publicly accessible datasets and complemented with real- world
world samples collected from open-source marine repositories. The dataset encompasses diverse species, lighting conditions, and
water depths.

Diffusion-Based Underwater Image Enhancement: A forward-reverse diffusion probabilistic model is applied to restore visual
clarity
Forward Process: Gradually adds Gaussian noise to model image degradation.
Reverse Process: Iteratively denoises the image, reconstructing color, detail, and contrast

Feature Extraction and Categorization (MobileNetV2): The enhanced images are processed using a MobileNetV2 architecture
due to its:

- Depthwise separable convolutions
- Reduced parameter count
- Suitability for mobile deployment

The network is fine-tuned using transfer learning, with frozen base layers and trained classification layers.

Performance Evaluation: Enhancement quality is validated using:

- PSNR (Peak Signal-to-Noise Ratio)
- SSIM (Structural Similarity Index)
- UIQM (Underwater Image Quality Measure)
- UCIQE (Underwater Color Image Quality Evaluation)

The classification performance was measured using accuracy, precision, recall, and F1-score.

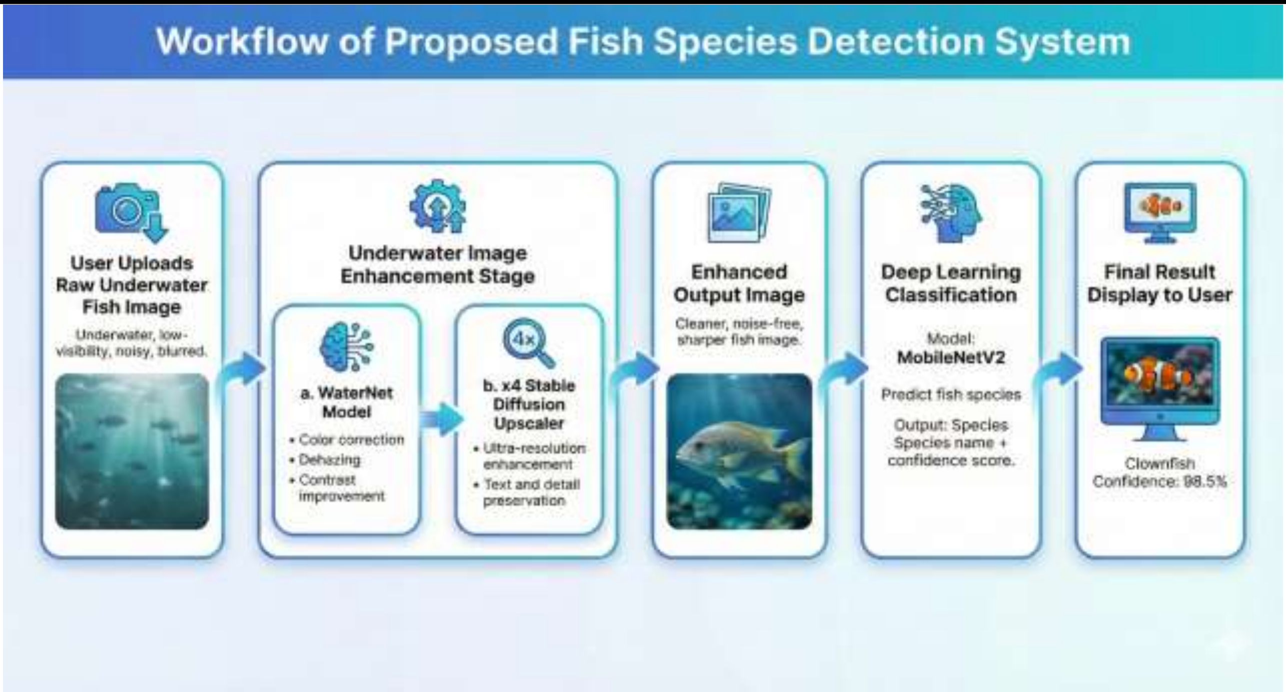

Fig1. Workflow of proposed fish species detection system

IV. RESULT AND DISCUSSION

The diffusion model significantly improved visual quality across all evaluation metrics. Enhanced images exhibited higher UIQM and UCIQE scores, indicating better color reproduction and improved perceptual quality

MobileNetV2 demonstrated strong classification performance after enhancement, with accuracy improving by up to 12–18% compared to models trained on unprocessed images. The combination of enhancement and classification resulted in clearer boundaries, more distinguishable texture patterns, and higher robustness to noise

Qualitative analysis demonstrates improved detection consistency under low-light and turbid conditions. Quantitative evaluation indicates that the proposed approach surpasses baseline CNN models, highlighting the importance of preprocessing through diffusion- based enhancement

Fig 2 : Input vs WaterNet vs WaterNet+Diffusion

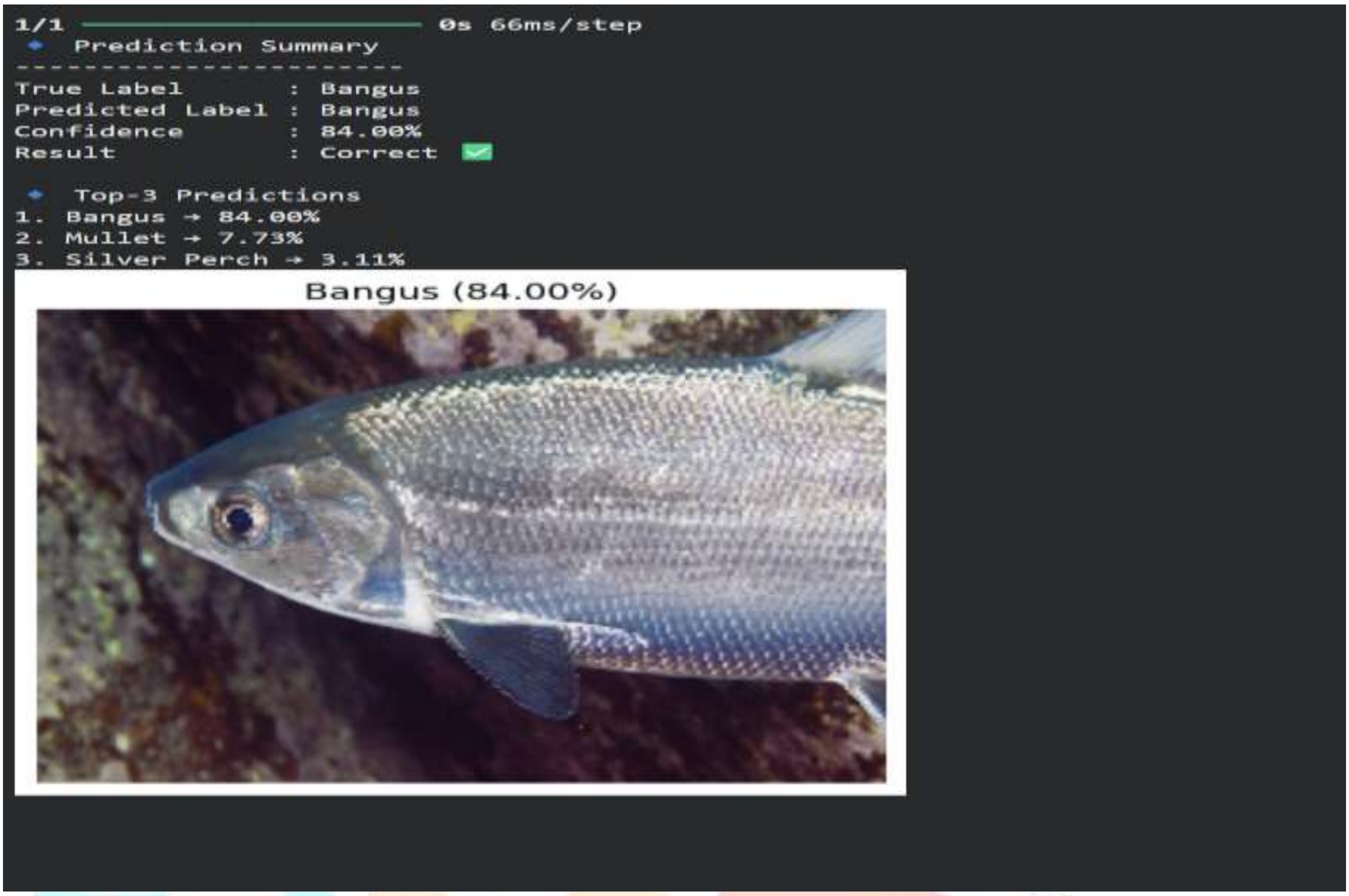

Fig 3: Fish Species Image Enhancement Metrics

Image	PSNR	SSIM	UIQM	UCIQE
Raw Input	12.3	0.42	1.9	0.54
WaterNet Output	18.7	0.61	2.45	0.62
WaterNet+Diffusion Output	22.3	0.71	3.01	0.74

Fig 4: Fish Species Prediction Analysis(MobileNetV2)

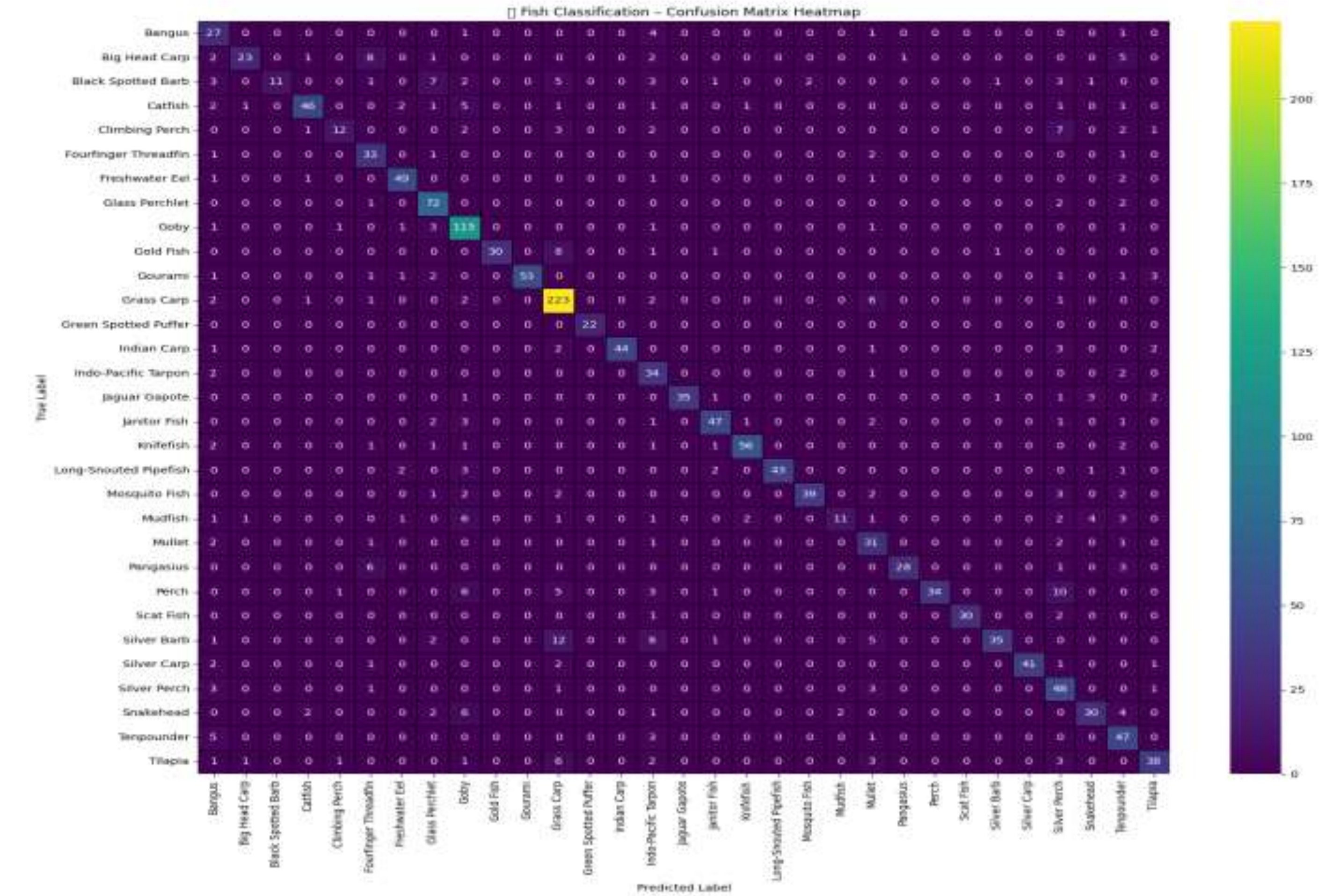

Fig 5: Confusion Matrix Analysis of Deep Learning-Based Fish Classification System

V. CONCLUSION

This study presents an integrated framework for underwater fish species detection that leverages diffusion-based enhancement and a MobileNetV2 classifier. The proposed system effectively resolves the challenges of underwater image degradation and significantly improves species recognition accuracy.

Owing to its lightweight architecture and high image restoration capability, the system is suitable for real-time marine monitoring, aquaculture automation, and underwater robotics.

VI. REFERENCES

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