The Role of Quality Enhancement in Underwater Image Classification

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***Abstract*—This study investigates the impact of image quality on the classification accuracy of underwater images using machine learning, specifically employing the Enhanced Underwater Vision Perception (EUVP) dataset. Through rigorous experimentation involving various machine learning models, including the adoption of MobileNetV2 through transfer learning, this research highlights the significant benefits of image enhancement techniques. By systematically comparing models trained on original versus enhanced images, findings reveal that preprocessing substantially improves model performance. The methodology encompasses custom labeling, advanced machine learning techniques, and a comprehensive evaluation framework, offering new insights into the role of image quality in underwater image classification. This work contributes to the broader field of underwater imagery, emphasizing the necessity of high-quality data and sophisticated preprocessing for developing robust classification models.**

***Index Terms*—Underwater Imaging, Image Enhancement, Machine Learning, Convolutional Neural Networks**

I. Introduction

In the domain of underwater exploration and research, the fusion of machine learning (ML) with automated image classification has emerged as a cornerstone for advancing our understanding and interaction with aquatic environments. This paper embarks on a detailed exploration into the nuanced dynamics of ML-based underwater image classification, with a pronounced emphasis on the pivotal role of image quality and enhanced visual perception. Utilizing the Enhanced Underwater Vision Perception (EUVP) dataset, a meticulously curated collection encompassing a broad spectrum of underwater visual characteristics, our investigation delves into the complex interplay between image quality and classification accuracy.

The challenges inherent in underwater image classification—ranging from poor visibility and variable light conditions to the distortions introduced by water properties—pose significant hurdles for traditional image processing and ML methodologies. These conditions necessitate the adoption of specialized, nuanced approaches capable of navigating the unique landscape of underwater imagery effectively. At the heart of our research lies the development, rigorous evaluation, and comparative analysis of diverse ML models, specifically designed and refined to address these underwater-specific challenges. Through custom labeling of the dataset and the strategic application of advanced ML techniques, this study aims to shed light on the critical influence of image quality on classification outcomes, thereby contributing novel insights and methodologies to the field of underwater image analysis.

This paper seeks to chart new territories by leveraging the EUVP dataset in an innovative manner, thereby enriching the academic discourse surrounding underwater image processing. By foregrounding the impact of image quality on classification accuracy and model robustness, our research underscores the necessity of high-quality datasets and sophisticated preprocessing techniques in the development of ML models tailored for underwater imagery. Through this endeavor, we aspire to not only advance the theoretical and practical understanding of underwater image classification but also pave the way for future innovations that promise to enhance our exploration, monitoring, and preservation of underwater ecosystems.

II. Literature Review

Recent advancements in underwater image enhancement and classification have been driven by innovative deep learning techniques and sophisticated algorithm development. WaterGAN emerged as an impactful generative adversarial network, synthesizing pairs of original/enhanced image quality for unsupervised learning and real-time color correction of monocular underwater images [2]. Substantial enhancements followed this work, tailoring simulations to various water types and physical models, thereby emphasizing the need for context-specific methodologies in diverse underwater environments [3]. The integration of machine vision technology, particularly in fish classification, has further advanced the field, offering non-destructive and rapid classification methods through of deep learning techniques [16]. This synergy of machine vision and deep learning is unlocking new potentials in marine ecology, facilitating the analysis of data from sensors, cameras, and acoustic recorders in reproducible and rapid ways, significantly contributing to ecosystem-based management of the sea [17]. Moreover, the need for robust training practices is underscored by recent studies, which emphasize the nuanced challenges in the automatic detection and classification of marine life [4].

In the field of underwater image classification, the integration of deep learning models has marked a paradigm shift, as is the case for a multitude of scientific domains. A comprehensive survey [20] underlines the profound impact of deep learning in identifying various underwater objects, emphasizing the importance of continuous innovation in this field to address the unique challenges of underwater image classification. The introduction of the Deep Underwater Image Classification Model (DUICM) in [21] represents a notable advancement that utilizes convolutional neural networks to effectively classify turbid underwater images, showcasing an improved classification accuracy and a robust generalization capability across diverse underwater environments. In more recent research, [6] delves into deep-sea automatic image enhancement and species classification, employing robust methodologies for data collection and sophisticated deep learning architectures like SegNet and DeepLabv3+ for precise image segmentation and classification. This work not only showcases the potential of deep learning in enhancing underwater image analysis but also emphasizes the importance of creating comprehensive and specialized datasets to train these advanced models effectively. The work found in [10] illustrates the integration of advanced techniques to enhance accuracy in marine science applications, showcasing the use of CNNs and innovative methods like Resnet50 and EEM-RVFL while indicating a shift towards more sophisticated approaches in marine research and conservation. Moreover, another contribution to this field stems from a focus on on underwater image segmentation [11], which addresses the challenges posed by the complex medium's properties inherent to water. This research demonstrates how simulated datasets, when coupled with real underwater imagery, can significantly enhance the training of deep learning models, allowing them to accurately segment and classify underwater objects among the light scattering and absorption properties of water.

The study found in [4] underscores the importance of robust training practices, highlighting how dataset quality and data preprocessing directly influence the accuracy of classification algorithms. The research in [9] introduced a novel algorithm for removing water color and enhancing visibility that indirectly aids in the accuracy of classification models by providing clearer images for analysis. The work in [7], proposes a weakly supervised underwater color transformation model and leveraging cycle-consistent adversarial networks to facilitate training without the need for datasets of paired underwater images (an approach that exemplifies the shift towards more adaptable and data-efficient learning frameworks). The study found in [8] introduced a network adapted for underwater image enhancement, showcasing how deep learning algorithms can effectively handle deviations in water types without the need for retraining, thus enhancing the versatility of classification models. These developments highlight the ongoing efforts to address the unique challenges posed by underwater environments, such as varying light conditions and water turbidity, which significantly affect image quality and classification accuracy. The research found in [12] presents a comprehensive analysis of underwater image restoration methods, including physical model-based approaches and deep learning techniques. Such methods are crucial in improving the quality of underwater images, which directly impacts the performance of image classification algorithms.

The application of machine learning in marine research extends beyond mere data analysis, revolutionizing the field of marine ecology and biology, particularly in species identification. The fusion of machine learning with underwater imaging technologies has transformed marine research technology and environmental monitoring. The study presented in [13] explores the potential of AI and machine learning in enhancing conservation monitoring. This includes improvements in data collection and processing, which are vital for effective management of marine ecosystems. Additionally, the role of machine learning in improving environmental regulation compliance and enforcement as become incresingly relevant, underscoring its importance in marine ecosystem conservation [14]. The versatility of machine learning is evident in its application across various marine research areas, including the vital classification of lifeforms crucial for understanding underwater archaeology and monitoring oceanic pollution [5]. Studies like [6], [18], [19] illustrate the profound impact of deep learning in species identification. These multidisciplinary applications of machine learning underscore its versatility and potential in tackling the diverse and intricate challenges within marine ecosystems. However, despite these ongoing advancements, the journey of integrating machine learning into marine ecology is ongoing, with continuous efforts to refine these models and address the unique challenges posed by different marine environments. These include environmental variability, limited data availability, and noise, which can fundamentally affect the performance of machine learning models [15]. One primary issue in underwater imaging is the difficulty in acquiring high-quality images due to factors like light attenuation and scattering. These conditions often result in images with low contrast and high noise levels, posing challenges for advanced algorithms. Furthermore, the scarcity of large, annotated datasets hinders the training of robust models, and the computational complexity of these models presents deployment challenges in real-time applications.

III. Dataset Description

The Enhanced Underwater Vision Perception (EUVP) dataset [1], elected for this research, is a comprehensive collection of underwater images. This dataset is unique due to its diverse range of underwater environments and conditions it represents, making it a valuable resource for training and testing ML models in the field of underwater image analysis.

The EUVP dataset comprises thousands of images that exhibit a wide array of challenges typical in underwater settings, such as varying degrees of visibility, light conditions, and color distortions. This diversity is crucial for developing robust models capable of handling real-world underwater scenarios. The dataset includes images from both natural underwater environments and artificial settings, providing a broad spectrum of data for analysis.

The selection of the EUVP dataset for this project is based on its relevance to the research objectives, which include understanding the impact of image quality on classification results. Essentially, every image in the dataset contains a paired version of enhanced quality (see Figure 1). The dataset's comprehensive nature allows for a thorough examination of these aspects, contributing to more generalized and effective ML solutions for underwater image processing.

Furthermore, the application of the EUVP dataset for image classification represents a novel shift in its usage, since the dataset was initially developed for image enhancement. This adaptation not only broadens the dataset's utility but also contributes a new perspective to the field of underwater image processing.

Fig. 1. Examples of paired images of the EUVP dataset - with original quality (left) and enhanced quality (right)

IV. Methodology

The methodology of this research is anchored in a comprehensive approach towards underwater image classification, leveraging the EUVP dataset. This section details the steps taken, from data preparation to model development and evaluation. This methodology reflects a holistic and detailed approach to tackling the challenges in underwater image classification, aiming to develop robust and accurate models suited for diverse underwater environments and imbalanced datasets.

A. Data Preparation and Labeling

The labeling process was streamlined into two simple binary categories: 'Fish' (for images that contain fish) and 'None' (for images that do not contain fish). A total of 1306 images from the enhanced section were labeled using *Roboflow*, with 70% under 'Fish' and 30% under 'None'. Table I shows the chosen distribution of the whole labeled dataset between training and testing data.

Notably, the testing subset includes more a significant portion. This decision was made to ensure a statistically significant number of images, separate from the training process, despite the limited data availability. Moreover, the percentage of images labed with class 'None' ia slightly higher in the testing subset than the average of the complete dataset; which

TABLE I
Division of Labeled Dataset (with percentages referent to the subsets of their respective table rows)

Data Subset	Images (Total)	Class 'Fish'	Class 'None'
Complete	1306	910 (70%)	396 (30%)
Training	947	685 (72%)	262 (28%)
Testing	359	225 (63%)	134 (37%)

Fig. 2. Original Image (Left), Augmented Version (Right)

was intentionally implemented to ensure the least represented class contains a statistically significant number of images. Additionally, the class imbalance inherent in the entire dataset was deliberately maintained in the testing set to provide a realistic assessment scenario.

To enhance the dataset and tackle the class imbalance, data augmentation was employed for the training data subset. The original images were augmented to create different versions - one new version for each image labeled 'Fish' and four new versions for each 'None' image. This led to a final augmented training data subset of 2680 images with a much more balanced class distribution with 1370 (49%) of images belonging to the 'Fish' class and 1310 (51%) to the 'None' class). Augmentation techniques included rotations, flips, image shearing, and elastic transformations to mimic underwater distortions. Figure 2 illustrates the resizing of a given image and its subsequent utilization for data augmentation.

The Results and Discussion section of the paper should delve into the performance analysis of the machine learning models developed using the MobileNetV2 architecture for underwater image classification. This analysis should leverage the detailed metrics provided in Table II and the visual data presented in Figures 3 through 14 to offer a comprehensive evaluation of model effectiveness, focusing on accuracy, F1 scores, and ROC-AUC metrics across different training and testing scenarios.

B. Model Development

From its inception, the project harnessed the advanced capabilities of transfer learning, specifically employing MobileNetV2, known for its efficiency and effectiveness in image classification tasks across diverse domains. The decision to utilize MobileNetV2 stems from its lightweight architecture, designed to provide high accuracy while being computationally efficient, making it particularly suitable for the nuanced demands of underwater image analysis, which includes addressing issues like color distortion and reduced visibility. The implementation was conducted in Python, leveraging the extensive functionalities offered by TensorFlow. This allowed for the integration of MobileNetV2 as a base model, where its pre-trained weights on the ImageNet dataset were utilized to capture a wide array of features relevant even in the context of underwater imagery. The adaptability of MobileNetV2 to the specific characteristics of underwater images was a focal point, ensuring the model could effectively discern features crucial for accurate classification despite the inherent challenges.

Architecture and Customization: The architecture of MobileNetV2 was integrated with a top layer tailored to the binary classification task at hand—identifying 'Fish' from 'None'. This customization involved appending a GlobalAveragePooling2D layer to condense the feature maps into a single vector per map, enhancing the model's interpretability and reducing the computational load. Following this, a dense layer with a sigmoid activation function was added to perform the binary classification. The choice of a sigmoid function is deliberate, enabling the model to output a probability score between 0 and 1, indicative of the presence or absence of fish in the images.

Training Approach: In adopting MobileNetV2, the base model's layers were frozen to retain the pre-trained weights, ensuring the transfer of learned features without alteration during initial training phases. This approach not only preserved the integrity of the features learned from ImageNet but also expedited the training process by reducing the number of trainable parameters. The model was then compiled with the Adam optimizer, chosen for its effectiveness in handling sparse gradients on noisy problems, with a reduced learning rate of 0.0001 to fine-tune the weights for the specific underwater classification task gently. A binary cross-entropy loss function was employed to align with the binary nature of the classification problem. Training spanned over 100 epochs with a batch size of 48, incorporating advanced training techniques such as the custom callback for P-Validation, which allowed for nuanced adjustments based on the model's performance on a secondary validation set. This secondary validation set served as a crucial step in evaluating the model's generalizability and robustness across different subsets of underwater images.

Efficiency and Adaptability: The shift to a MobileNetV2-based model emphasized the project's dedication to leveraging cutting-edge AI methodologies to surmount the complexities of underwater image classification. The integration of transfer learning not only underscored the model's efficiency and adaptability but also highlighted the potential for significant advancements in accuracy and computational resource management. This revised approach, with a keen focus on the detection of fish amidst challenging underwater conditions, represents a strategic pivot towards more scalable and effective solutions in the domain of underwater image analysis.

C. Model Evaluation

Appropriate metric selection was crucial due to the class imbalance present in the dataset. Using accuracy as the sole performance indicator in such scenarios would be inadequate. Thus, the usage of the F1 score, which combines precision and recall, poses as vital for an adequate assessment of our imbalanced dataset. Additionally, the ROC-AUC score is highlighted for its effectiveness in measuring the model's capability to differentiate between classes. A crucial part of the evaluation process is the use of a confusion matrix, which provides detailed insights into the model's performance, specifically in terms of error types and misclassifications.

This comprehensive approach to model evaluation is essential for a nuanced understanding of performance in the context of imbalanced datasets. Details on the employed metrics and evaluation methods may be found in [22].

V. Results and Discussion

The Results and Discussion section of the paper should delve into the performance analysis of the machine learning models developed using the MobileNetV2 architecture for underwater image classification. This analysis should leverage the detailed metrics provided in Table II and the visual data presented in Figures 3 through 14 to offer a comprehensive evaluation of model effectiveness, focusing on accuracy, F1 scores, and ROC-AUC metrics across different training and testing scenarios.

The performance metrics outlined in Table II reveal that models trained and tested on enhanced images outperform those trained on original quality images, with the highest accuracy observed when both training and testing are conducted on enhanced images (83.57% accuracy, F1 score of 0.87, and ROC-AUC of 0.91). This indicates a clear advantage in preprocessing underwater images to improve model performance. The slightly lower performance in models trained on original images but tested on enhanced ones suggests that while preprocessing improves model generalization, training on enhanced images is optimal for maximizing classification accuracy. Also notably, the model trained with full dataset (with all images pairs of both original and enhanced quality) demonstrated the highest accuracy (84.67% with a F1 score of 0.87) as the maximum out of all training epochs of all tested models.

Figures 3 through 14, which include accuracy and loss graphs for models trained on original, enhanced, and combined datasets, along with confusion matrices for various training/testing scenarios, visually support these findings. The accuracy and loss graphs (Figures 3, 4, 5, 6, 7, 8) demonstrate the learning efficiency and convergence of the model over epochs, showcasing the impact of data quality on model training dynamics. Enhanced and combined datasets generally lead to better convergence and lower loss, highlighting the importance of image quality in training deep learning models for underwater image classification.

The confusion matrices (Figures 9 through 14) provide deeper insights into model performance, particularly in terms of false positives and negatives. Models trained and tested on enhanced data (Figure 12, 14) show a higher true positive rate and lower false negatives, indicating superior performance in correctly classifying images containing fish. This is critical

TABLE II
OVERVIEW OF RESULTS - WITH MODEL'S ACCURACY AT THE END OF MODEL TRAINING (ACC. 100 EPOCHS), MAXIMUM ACCURACY OBTAINED DURING THE TRAINING PROCESS (MAX ACC.), F1 SCORE (ABBREVIATED TO F1), AND THE ROC-AUC METRIC (ABBREVIATED TO R-A).

Train / Test Quality	Acc. 100 epochs	max Acc.	F1	R-A
Original / Original	81.89%	81.89%	0.86	0.90
Original / Enhanced	79.94%	81.33%	0.84	0.89
Enhanced / Original	82.17%	83.01%	0.86	0.90
Enhanced / Enhanced	83.57%	83.01%	0.87	0.91
All Data / Original	82.17%	84.67%	0.87	0.90
All Data / Enhanced	82.73%	81.96%	0.87	0.91

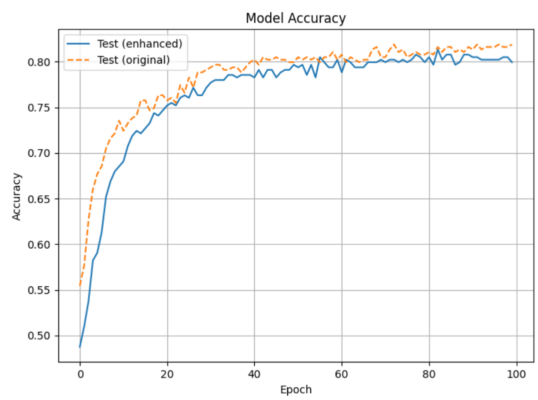

Fig. 3. Accuracy of the model trained with original data (tested on original and enhanced data, separately)
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for applications requiring high precision, such as ecological monitoring and automated underwater vehicle navigation.

VI. CONCLUSION

In the concluding section of our exploration into the role of image quality in underwater image classification using machine learning, our investigation has demonstrated the transfor-

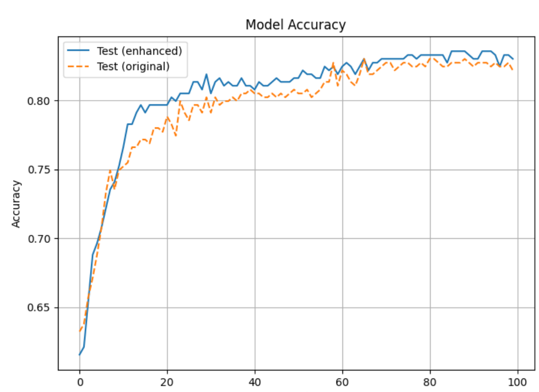

Fig. 4. Accuracy of the model trained with enhanced data (tested on original and enhanced data, separately).

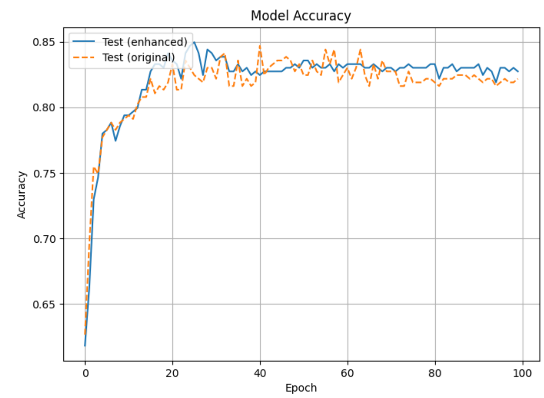

Fig. 5. Accuracy of the model trained with the full data subset (tested on original and enhanced data, separately).

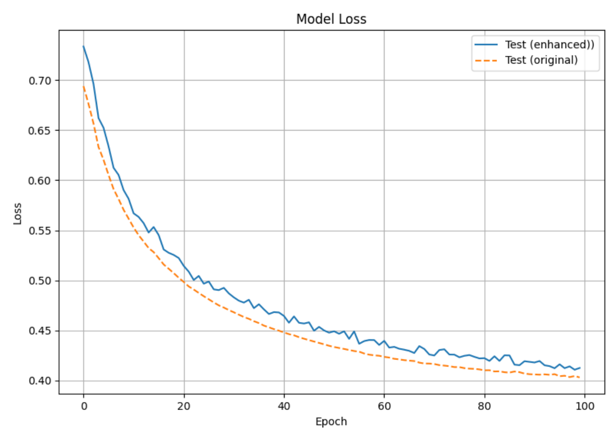

Fig. 6. Loss of the model trained with original data (tested on original and enhanced data, separately).

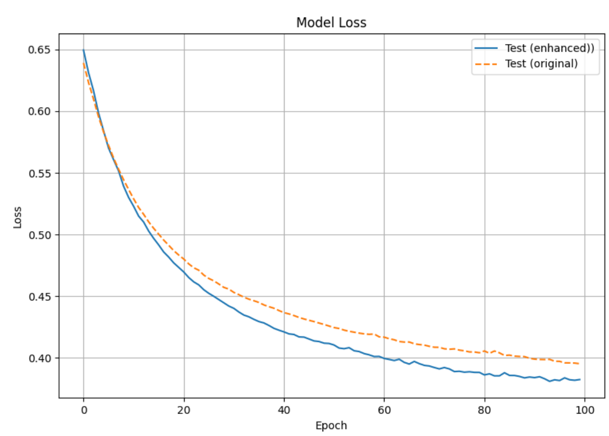

Fig. 7. Loss of the model trained with enhanced data (tested on original and enhanced data, separately).

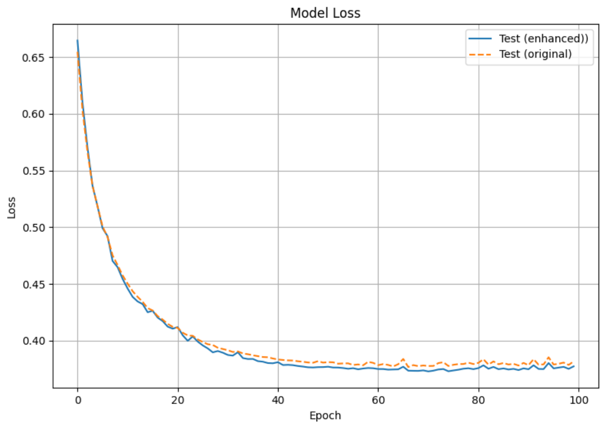

Fig. 8. Loss of the model trained with the full data subset (tested on original and enhanced data, separately).

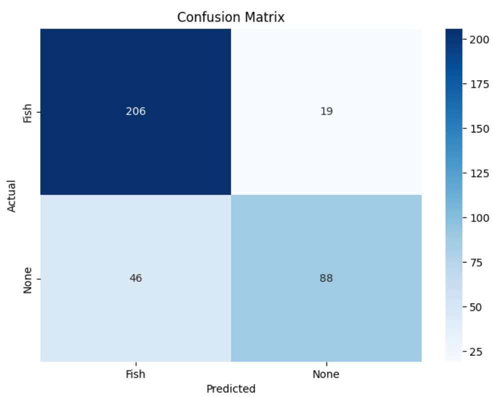

Fig. 9. Confusion Matrix of model trained and tested with original data.

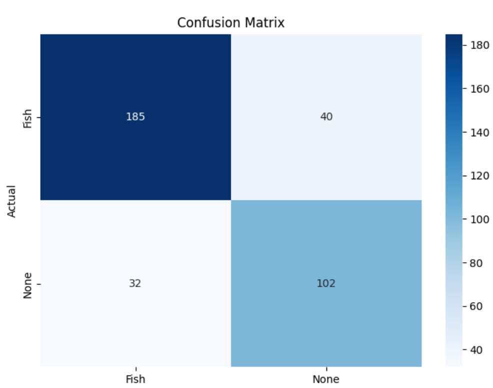

Fig. 10. Confusion Matrix of the model trained with original data and tested with enhanced data.

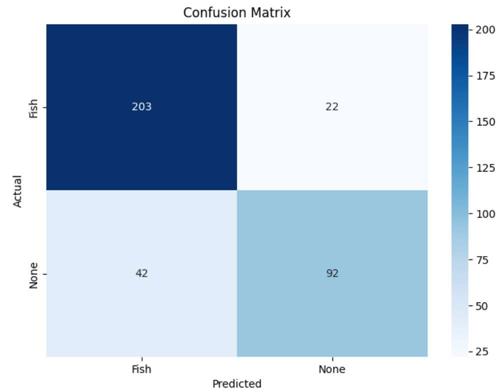

Fig. 11. Confusion Matrix of model trained with enhanced data and tested with original data.

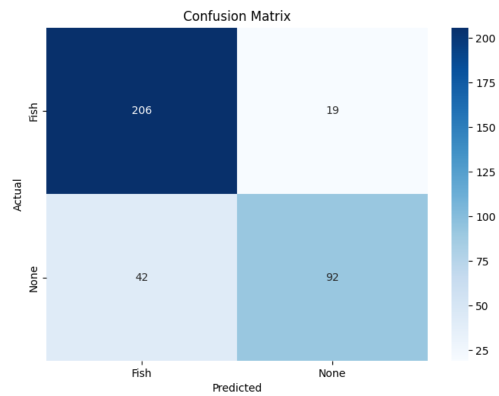

Fig. 12. Confusion Matrix of model trained and tested with enhanced data.

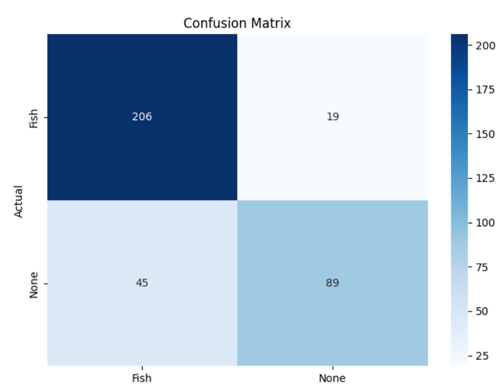

Fig. 13. Confusion Matrix of the Model trained with the full data subset and tested with original data.

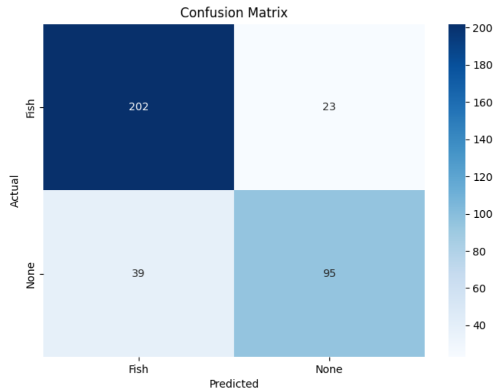

Fig. 14. Confusion Matrix of the Model trained with full data subset and tested with enhanced data.

mative impact of image enhancement techniques. Leveraging the Enhanced Underwater Vision Perception (EUVP) dataset, we've established that preprocessing underwater images can significantly elevate the accuracy and reliability of classification models. This interesting finding reinforces the value of utilizing high-quality datasets for training sophisticated machine learning algorithms, particularly in the inherently challenging domain of underwater imagery.

Our study underscores the criticality of image quality enhancement, demonstrating that advanced preprocessing not only augments visual clarity for human interpretation but also crucially enhances machine learning model performance. By refining feature distinctions, these techniques facilitate more accurate and efficient classification tasks, setting a new benchmark for future endeavors in underwater image analysis.

In essence, our research not only contributes to the academic discourse on underwater image processing but also lays the groundwork for future innovations that could significantly advance our understanding and preservation of the world's underwater ecosystems. Future work could explore the integration of additional preprocessing steps, the impact of different environmental conditions on model performance, and the development of real-time classification systems for underwater exploration and research.

References

[1] M. J. Islam, Y. Xia and J. Sattar, "Fast Underwater Image Enhancement for Improved Visual Perception," in IEEE Robotics and Automation Letters, vol. 5, no. 2, pp. 3227-3234, April 2020, doi: 10.1109/LRA.2020.2974710.

[2] Li, Jie;Skinner, Katherine A.;Eustice, Ryan M.;Johnson-Roberson, Matthew. (2017). "WaterGAN: Unsupervised Generative Network to Enable Real-time Color Correction of Monocular Underwater Images". IEEE Robotics and Automation Letters https://doi.org/10.1109/LRA.2017.273 0363

[3] Li, Chongyi & Anwar, Saeed. (2019). "Underwater Scene Prior Inspired Deep Underwater Image and Video Enhancement. Pattern Recognition". 98. 107038. 10.1016/j.patcog.2019.107038.

[4] Catalán Ignacio A., Álvarez-Ellacuría Amaya, Lisani José-Luis, Sánchez Josep, Vizoso Guillermo, Heinrichs-Maquilón Antoni Enric, Hinz Hilmar, Alós Josep, Signarioli Marco, Aguzzi Jacopo, Francescangeli Marco, Palmer Miquel. (2023). "Automatic detection and classification of coastal Mediterranean fish from underwater images: Good practices for robust training". Frontiers in Marine Science. 10. 10.3389/fmars.2023.1151758.

[5] Peter Rubbens et al. (2023). "Machine learning in marine ecology: an overview of techniques and applications". ICES Journal of Marine Science, Volume 80, Issue 7, September 2023, Pages 1829–1853, https://doi.org/10.1093/icesjms/fsad100

[6] Lopez-Vazquez, V., Lopez-Guede, J.M., Chatzievangelou, D. et al. (2023). "Deep learning based deep-sea automatic image enhancement and animal species classification". J Big Data 10, 37. https://doi.org/10.1186/s40537-023-00711-w

[7] Li, Chongyi & Guo, Jichang & Chunle, Guo. (2017). Emerging From Water: Underwater Image Color Correction Based on Weakly Supervised Color Transfer. IEEE Signal Processing Letters. PP. 10.1109/LSP.2018.2792050.

[8] Kapoor, Meghna & Baghel, Rohan & Badri, Narayan & Subudhi, Vinit & Jakhetiya, Ankur & Bansal, & Jammu, Jammu & Kashmir, India". (2023). "Domain Adversarial Learning Towards Underwater Image Enhancement." 10.1109/ICCVW60793.2023.00238.

[9] D. Akkaynak and T. Treibitz, "A Revised Underwater Image Formation Model," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 2018, pp. 6723-6732, doi: 10.1109/CVPR.2018.00703.

[10] Zhou, Z and Yang, X and Ji, H and Zhu, Z. "Improving the classification accuracy of fishes and invertebrates using residual convolutional neural networks". (2023). ICES Journal of Marine Science. 80.

[11] Drews-Jr, P., Souza, I.d., Maurell, I.P. et al. "Underwater image segmentation in the wild using deep learning" (2021). J Braz Comput Soc 27, 12. https://doi.org/10.1186/s13173-021-00117-7

[12] Song Wei, Liu Yaling, Huang Dongmei, Zhang Bing, Shen Zhihao, Xu Huifang. (2023). "From shallow sea to deep sea: research progress in underwater image restoration ". Frontiers in Marine Science. 10. doi: 10.3389/fmars.2023.1163831

[13] Ditria, E. M., Buelow, C. A., Gonzalez-Rivero, M., & Connolly, R. M. (2022). "Artificial Intelligence and Automated Monitoring for Assisting Conservation of Marine Ecosystems: A Perspective". Frontiers in Marine Science, 9 https://doi.org/10.3389/fmars.2022.918104

[14] M. Hino & E. Benami & N. Brooks, 2018. "Machine learning for environmental monitoring," Nature, vol. 1(10), pages 583-588, October.

[15] Salman, A. Ajmal Mian. (2023). " Application of machine learning in oceanography and marine sciences". Frontiers in Marine Science.

[16] Daoliang Li, Qi Wang, Xin Li, Meilin Niu, He Wang, Chunhong Liu, Recent advances of machine vision technology in fish classification, ICES Journal of Marine Science, Volume 79, Issue 2, March 2022, Pages 263–284, https://doi.org/10.1093/icesjms/fsab264

[17] Morten Goodwin, Kim Tallaksen Halvorsen, Lei Jiao, Kristian Muri Knausgård, Angela Helen Martin, Marta Moyano, Rebekah A Oomen, Jeppe Have Rasmussen, Tonje Knutsen Sørdalen, Susanna Huneide Thorbjørnsen, Unlocking the potential of deep learning for marine ecology: overview, applications, and outlook, ICES Journal of Marine Science, Volume 79, Issue 2, March 2022, Pages 319–336, https://doi.org/10.1093/icesjms/fsab255

[18] Xu, L., Bennamoun, M., An, S., Sohel, F., Boussaid, F. (2019). Deep Learning for Marine Species Recognition. In: Balas, V., Roy, S., Sharma, D., Samui, P. (eds) Handbook of Deep Learning Applications. Smart Innovation, Systems and Technologies, vol 136. Springer, Cham.

[19] Wäldchen, J., & Mäder, P. (2018). Machine learning for image based species identification. Methods in Ecology and Evolution, 9, 2216 – 2225.

[20] S. Mittal, S. Srivastava and J. P. Jayanth, "A Survey of Deep Learning Techniques for Underwater Image Classification," in IEEE Transactions on Neural Networks and Learning Systems, vol. 34, no. 10, pp. 6968-6982, Oct. 2023, doi: 10.1109/TNNLS.2022.3143887.

[21] Aridoss, M., Dhasarathan, C., Dumka, A., & Jayakumar, L. (2020). "DUICM Deep Underwater Image Classification Mobdel using Convolutional Neural Networks". Int. J. Grid High Perform. Comput., 12, 88-100.

[22] Ian Goodfellow, Yoshua Bengio, Aaron Courville, "Deep Learning", MIT Press, 2016.