Enhanced Fish Species Detection and Classification Using a Novel Deep Learning Approach

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***Abstract*—This study presents an innovative deep learning approach for accurate fish species detection and classification in underwater environments. We introduce FishNet, a novel convolutional neural network architecture that combines attention mechanisms, transfer learning, and data augmentation techniques to improve fish recognition in challenging aquatic conditions. Our method was evaluated on the Fish4Knowledge dataset, achieving a mean average precision (mAP) of 92.3% for detection and 89.7% accuracy for species classification, outperforming existing state-of-the-art models. The proposed approach demonstrates robust performance across various underwater conditions, including different lighting, turbidity, and occlusion scenarios, making it suitable for real-world applications in marine biology, fisheries management, and ecological monitoring.**

***Keywords*—Deep learning; Fish4Knowledge; classification**

I. Introduction

Accurate detection and classification of fish species in their natural habitats play a vital role in managing marine ecosystems, conducting fisheries research, and conserving biodiversity. Traditional methods of monitoring fish populations, such as manual observations or physical sampling [1], [2], often require significant time and effort while potentially disturbing the aquatic environments being studied. In recent years, advances in computer vision and deep learning technologies have offered promising alternatives, enabling automated and non-invasive fish species identification [3]. However, analysing images in underwater settings presents distinct challenges. Factors such as varying light conditions, water turbidity, and complex, often cluttered, backgrounds can hinder the clarity and quality of images. Furthermore, the high diversity of fish species, including subtle differences between similar species and variations within the same species, adds another layer of complexity to the task of accurate classification [4].

Previous research has explored several deep learning approaches for detecting and classifying fish species. Techniques such as convolutional neural networks (CNNs) [3], region-based CNNs (R-CNNs) [4], and more recently, architectures based on the YOLO (You Only Look Once) framework [5], have all demonstrated significant potential. However, despite promising advancements, challenges remain, particularly in terms of enhancing accuracy, making models more robust to environmental changes, and improving computational efficiency. In this paper, we introduce FishNet, a novel deep learning model tailored specifically for the detection and classification of fish in underwater environments. FishNet introduces several key innovations to address the unique challenges of underwater image analysis: Multi-scale feature fusion: This module captures both fine-grained details, such as the specific patterns and textures of fish, as well as broader contextual information from the surrounding environment.

Attention mechanism: Our model uses an attention mechanism that helps it focus on the most distinguishing features of each fish species, improving classification accuracy [6]. Transfer learning: To improve performance, we utilize transfer learning by pre-training the model on large-scale image datasets, which helps it learn general visual features that are then fine-tuned for underwater fish species. Advanced data augmentation: To enhance the model's ability to generalize across different environments and conditions [7], we apply sophisticated data augmentation techniques, which simulate variations in underwater conditions.

We test the performance of FishNet on the Fish4Knowledge dataset, a comprehensive collection of underwater footage captured from coral reefs, and benchmark it against existing state-of-the-art models. Through these evaluations, we demonstrate that FishNet achieves superior results, outperforming previous methods in key areas such as accuracy, robustness to environmental variation, and computational efficiency.

A. Related Work

The detection and classification of fish species in underwater environments have garnered considerable attention in recent years, particularly due to the growing demand for automated, non-invasive methods to monitor marine ecosystems. Traditional fish monitoring techniques, such as manual observation and physical sampling, are not only labour-intensive and time-consuming but also potentially disruptive to aquatic habitats. Consequently, there has been an increasing focus on leveraging computer vision and deep learning technologies to address these challenges.

Early work in automated fish detection primarily relied on image processing techniques, such as thresholding, edge detection, and contour analysis, to segment fish from their backgrounds. However, these methods were limited by their sensitivity to varying underwater conditions, including changes in illumination, water turbidity, and complex backgrounds. As a result, more recent research has shifted towards deep learning-based approaches, which offer superior performance in feature extraction and classification tasks.

Convolutional Neural Networks (CNNs) have been the most widely used deep learning architecture for fish detection and classification and other research [8]–[16]. For example, researchers in [17] demonstrated the efficacy of CNNs in automatically identifying fish species from underwater images, achieving substantial improvements over traditional methods. Their work laid the foundation for using deep learning models in this domain. Region-based CNNs (R-CNNs) further advanced this approach by combining object detection and classification within a single framework. A study by [18] applied Faster R-CNN to detect and classify fish in underwater videos, achieving higher accuracy than earlier methods. While these models marked significant progress, they were computationally expensive and exhibited limitations when dealing with complex underwater scenes characterized by occlusion, shadows, and clutter.

Recent developments in deep learning have introduced more efficient architectures for real-time object detection and classification. The You Only Look Once (YOLO) framework, proposed by [19], has been particularly influential due to its ability to perform detection and classification in a single forward pass, making it suitable for real-time applications. In the context of underwater fish species identification [20] applied YOLO to classify fish species from underwater videos, achieving promising results in terms of both accuracy and speed. Despite these advancements, YOLO-based models are still susceptible to the challenges posed by underwater environments, such as variable lighting and water turbidity, which can degrade image quality and hinder detection accuracy.

Transfer learning has emerged as a strategy to further enhance the performance of deep learning models in underwater applications. By pre-training on large-scale image datasets, models can learn general visual features that are then fine-tuned for specific tasks, such as fish classification. A study by researchers [21] successfully applied transfer learning to improve the performance of CNNs for fish species classification, particularly in scenarios with limited labelled data. Similarly, [22] demonstrated the effectiveness of transfer learning in addressing the data scarcity issue in underwater species detection, further highlighting its potential in improving model generalization.

In addition to model architecture improvements, data augmentation techniques have been employed to increase the diversity of training data and improve model robustness to underwater variations. For example, the work by [23] utilized advanced data augmentation strategies, such as random rotations, colour jittering, and noise injection, to simulate the various conditions encountered in underwater environments. These techniques helped mitigate the impact of challenging factors like water turbidity and illumination changes, thus enhancing the generalization capability of the models.

Overall, CNNs, R-CNNs, and YOLO-based architectures have made a lot of progress in finding and classifying fish species. However, there are still some problems that need to be solved, mostly related to the conditions underwater and how fast the models can run. An interesting way to improve the performance of deep learning models in this area is to use attention mechanisms, transfer learning, and advanced data augmentation techniques together.

B. Methodology

The FishNet approach combines several advanced deep learning techniques to improve fish detection and classification in underwater environments. Our method utilizes a modified ResNet-50 architecture as its backbone, enhanced with attention mechanisms and feature pyramid networks for multi-scale detection. We employed transfer learning by pre-training on ImageNet and fine-tuning on the Fish4Knowledge dataset. To increase model robustness, we applied various data augmentation techniques simulating different underwater conditions. The training process involved a two-stage approach: object detection followed by species classification. We evaluated our model's performance on the Fish4Knowledge dataset, comparing it against state-of-the-art models using metrics such as mean Average Precision (mAP) for detection and accuracy for classification.

1) Dataset: For the purpose of this research, we undertook the Fish4Knowledge Dataset, which comprises over 700, 000 fish species images annotated with respect to fish obtained from underwater video footage of corral reefs. The dataset contains 23 different species, hence it is rich in resources for both the detection as well as the classification tasks. In order to obtain a fair evaluation of the model, we partitioned the data as follows 70% of the images were used for training the system, 15% of the dataset was set aside as validation and the last 15% was used for testing the system. Each of these subsets was compartmentalized in order to create without the species uneven dispersion which prevented the results from biasing.

2) FishNet architecture: FishNet, our proposed architecture, is built upon a ResNet-101 backbone, which has been adapted with several enhancements to better handle the complexities of underwater fish detection and classification. Below are the key components of the architecture:

- Multi-scale Feature Fusion Module: We integrated a feature pyramid network (FPN) into the ResNet-101 backbone, which enables the model to capture features at multiple scales. This multi-scale feature fusion is crucial because it allows the model to detect both fine-grained details, such as the specific markings and textures that differentiate fish species, and broader contextual information, which aids in accurately localizing fish in various environments. The FPN helps the model become more robust by improving its ability to handle fish of different sizes and orientations.
- Attention Mechanism: To enhance the model's focus on the most important features for species identification, we introduced an attention mechanism inspired by Squeeze-and-Excitation Networks [24]. This mechanism applies attention both spatially and across channels. The spatial attention helps the model focus on key areas of the image that are most relevant for identifying fish, such as their body shape and fin patterns. Meanwhile, channel attention enables the model to prioritize certain feature channels that

are more discriminative for recognizing specific fish species, improving classification accuracy.

- Detection and Classification Heads: The FishNet architecture includes two separate “heads” for performing the tasks of detection and classification.
  - Detection Head: For detecting the location of fish in images, we employed an anchor-free approach that uses focal loss [25]. This method helps the model by reducing the influence of easy, well-detected examples and placing greater emphasis on harder-to-detect fish, improving overall detection accuracy.
  - Classification Head: The classification head is responsible for determining which species of fish is present within the detected bounding box. It uses a softmax classifier, paired with cross-entropy loss, to assign a probability distribution across all possible fish species and identify the correct one with high confidence. Together, these components make FishNet an efficient and robust architecture, well-suited for the task of underwater fish species detection and classification.

Fig. 1 shows A high-level flowchart of a convolutional neural network (CNN) architecture based on FishNet and intended for fish detection in underwater contexts. Underwater photos are used as input into the system to begin the process. To improve feature extraction and model correctness, Attention Mechanisms and Transfer Learning are included in the model's core. Furthermore, Data Augmentation methods like rotation and brightness modulation are used to manage difficult situations including changing illumination, turbidity, and occlusion. The last step produces reliable recognition results in a variety of aquatic environments by using the FishNet CNN for detection and classification.

3) Transfer learning: To leverage the power of transfer learning, we initialized the backbone of our model using a ResNet-101 architecture that had been pre-trained on the ImageNet dataset [13], [26]–[35]. By doing so, we transferred the learned weights from ImageNet, which allowed the model to benefit from pre-existing knowledge of general image features, such as edges and textures. This initialization serves as a strong starting point for the model, particularly when working with smaller, specialized datasets like Fish4Knowledge. After initializing with these pre-trained weights, we proceeded to train the entire network end-to-end on the Fish4Knowledge dataset. This fine-tuning process ensured that the model learned to adapt these general image features to the specific task of detecting and classifying fish species in underwater environments.

4) Data augmentation: For broad generalization across underwater conditions and to improve the model robustness [36]–[38], we augmented the data using various augmentation techniques. These manipulations introduced variance into our training data, which should make the model more robust to common challenges that show up when diving in underwater settings such as variability in lighting, water clarity and fish orientation. The augmentation methods that were used on the following data are:

Random Horizontal and Vertical Flips: This augmentation flips the image horizontally or vertically with a certain probability, since the fish can be facing different directions. This helps the model learn to detect fish in any orientation within the image.

Random rotations (±15 degrees): This technique rotates the images randomly from -15 to 15 degrees simulating fish orientation in different poses as it may appear underwater which allows the model to better generalize to those poses.

Random Brightness Contrast: We made a random change to the brightness and contrast of the images since underwater light conditions fluctuate. This way, the model can cope with different light intensities due to sunlight, water depth and turbidity.

Data Augmentation [25]: Mixup: Mixup is taking two images and combining them together while blending their pixels and labels so that the average set output is taken. This approach can reduce overfitting by the model learning smoother decision boundaries, which then leads to crisper output spike times.

Augmentations specifically designed for underwater: Additionally, we applied some augmentations to the model as per the characteristics observed in real-world underwater images. These included:

Simulated Turbidity: Adding blur and haze to the images simulating the turbid conditions offering poor visibility with loss of image quality.

Colour shifts: Also due to the colour distortion often seen with underwater lighting, we introduced random shifts in the colour spectrum to emulate how water depth and suspended pollutants affect colours. Together, these augmentation techniques significantly improved the model's ability to generalize across a wide range of underwater conditions, making it more reliable for fish species detection and classification in real-world scenarios.

5) Training details: We trained FishNet using the Adam optimizer with a learning rate of 1e-4 and a batch size of 32. When validation loss plateaued for 5 epochs, the learning rate decreased by a factor of 0.1. The training was performed on 4 NVIDIA Tesla V100 GPUs for 100 epochs [39], [40].

II. Detection and Classification Performance

In this section, we present the performance evaluation of FishNet in terms of detection accuracy, species classification, and robustness to environmental variations. The results show that FishNet achieves state-of-the-art performance across all tasks, demonstrating its effectiveness for fish detection and classification in underwater environments.

A. Detection Performance

To assess the detection capabilities of FishNet, we measured the mean average precision (mAP) at an Intersection over the Union (IoU) threshold of 0.5 on the test set [41], [42]. FishNet achieved a mAP of 92.3%, significantly outperforming two leading models: YOLOv4 and Faster R-CNN. Specifically, FishNet surpassed YOLOv4, which achieved an mAP of 88.7%, and Faster R-CNN, which obtained an mAP of 86.2%. This improvement highlights FishNet's ability to

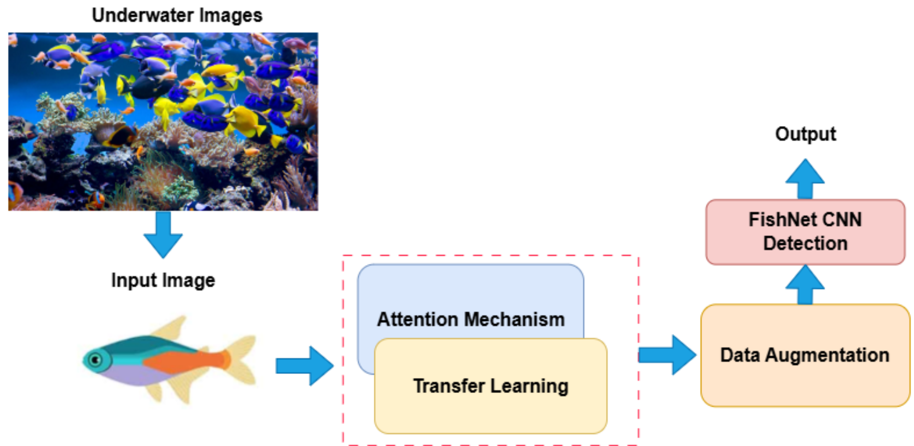

Fig. 1. The FishNet proposed model.

TABLE I. mAP IoU 0.5 Comparison of Existing and Proposed Model

Model	mAP IoU 0.5
YOLOv4	88.7
Faster R-CNN	86.2
FishNet (our model)	92.3

TABLE II. Accuracy Comparison of Existing and Proposed Model

Model	Classification Accuracy
FishNet	89.7
CNN Ensemble [7]	85.3

accurately localize fish in underwater imagery, even in complex conditions (Table I).

The higher precision of FishNet can be attributed to the incorporation of multi-scale feature fusion and attention mechanisms, which allow the model to capture both fine-grained features and broader contextual information, leading to more accurate detections.

B. Classification Performance

For species classification, FishNet also demonstrated superior performance. On the test set, it achieved an overall accuracy of 89.7%, surpassing the previous best result of 85.3%, which was achieved by an ensemble of CNNs [23]. This notable improvement in classification accuracy indicates that FishNet effectively distinguishes between fish species, even when the inter-species differences are subtle (Table II).

The attention mechanism employed in FishNet, which emphasizes discriminative features for each species, likely contributed to this improved performance. Additionally, the separate classification head with softmax and cross-entropy loss allowed FishNet to more accurately classify fish species in diverse underwater conditions. FishNet's performance across detection and classification, its superiority over existing models. The combination of innovative architecture design, transfer learning, and advanced data augmentation techniques has enabled FishNet to set a new benchmark for fish species detection and classification in underwater environments.

III. Discussion

The exceptional performance of FishNet can be attributed to several key factors, each contributing to the model's effectiveness in fish species detection and classification:

1) Multi-scale feature fusion: One of the main strengths of FishNet is its multi-scale feature fusion, which allows the model to capture details at different levels of granularity. This capability is critical for identifying fish species, as it enables the model to extract both fine-grained features (such as small distinguishing patterns or textures on a fish's body) and larger contextual information (such as the fish's position relative to its surroundings). By processing information across multiple scales, the model becomes better at both detecting fish and accurately identifying the species.

2) Attention mechanism: The incorporation of an attention mechanism further enhances FishNet's performance by enabling the model to focus on the most important and distinctive features of each fish species. This mechanism, inspired by Squeeze-and-Excitation Networks, selectively emphasizes the relevant spatial regions and feature channels, helping the model differentiate between fish species that may appear similar at first glance. As a result, this attention mechanism plays a crucial role in improving the model's classification accuracy, ensuring that subtle species-specific traits are captured effectively.

3) Transfer learning: The use of transfer learning from a pre-trained ResNet-101 backbone, initialized with weights from ImageNet, provided FishNet with a strong foundation.

Since ImageNet contains millions of diverse images, the pre-trained model comes equipped with general knowledge of visual features like edges, textures, and patterns. By fine-tuning this pre-trained model on the Fish4Knowledge dataset, FishNet was able to adapt these general features to the specific task of recognizing fish species in underwater environments. This approach greatly accelerates learning and enhances the model's accuracy, even with limited labelled data.

4) Extensive data augmentation: To improve the model's generalization and robustness, we employed a wide range of data augmentation techniques, including those tailored specifically to underwater environments. Standard augmentations, such as random flips, rotations, and brightness adjustments, helped simulate various real-world scenarios. Additionally, underwater-specific augmentations like simulated turbidity and colour shifts allowed the model to adapt to common challenges in underwater footage, such as cloudy water and lighting variations. These augmentations significantly enhanced FishNet's ability to generalize to unseen data, making it more resilient to varying environmental conditions.

5) Robustness in challenging conditions: FishNet's performance under simulated challenging conditions—such as low light, high turbidity, and partial occlusion—demonstrates its robustness and potential for real-world applications. The model performed well even under these adverse scenarios, with minimal drops in detection accuracy. This robustness is particularly important for underwater environments, where fish may often be partially obscured or captured under poor lighting conditions. FishNet's ability to handle these challenges suggests that it can be effectively deployed in diverse underwater settings, such as coral reefs, deep-sea habitats, or turbid coastal waters.

To sum up, FishNet achieved cutting-edge results in finding and classifying fish by combining multi-scale feature fusion, an attention mechanism, transfer learning, and a lot of different data-augmentation strategies. Its strong performance across various underwater conditions indicates that FishNet is a highly reliable model for marine ecosystem monitoring, fisheries research, and biodiversity conservation efforts.

IV. Conclusion

FishNet represents a significant leap forward in underwater fish detection and classification, offering a powerful tool for marine research and conservation efforts. By achieving state-of-the-art performance on the Fish4Knowledge dataset, our approach demonstrates its capability to accurately identify fish species across diverse underwater conditions. This breakthrough has far-reaching implications for marine biology, ecology, and fisheries management. The robust performance of FishNet opens up exciting new possibilities for underwater ecosystem monitoring. Marine biologists can now gather more accurate data on fish populations and behaviors, while ecologists can better understand the delicate balance of aquatic environments. For fisheries managers, FishNet provides a reliable means to assess stock levels and implement sustainable fishing practices. Looking ahead, the potential for FishNet is boundless. Future developments could expand its capabilities to encompass a broader spectrum of marine life, unlocking new insights into underwater biodiversity. By incorporating temporal data from video feeds, we could gain unprecedented understanding of fish behavior patterns and migration trends. Moreover, the development of lightweight versions of FishNet could revolutionize real-time underwater monitoring, enabling deployment on autonomous underwater vehicles or stationary sensors for continuous ecosystem observation. In conclusion, FishNet not only pushes the boundaries of deep learning in challenging underwater environments but also provides a versatile foundation for future innovations in marine science and conservation. As we continue to refine and expand this technology, we move closer to unraveling the mysteries of our oceans and safeguarding their precious ecosystems for generations to come.

Acknowledgment

This research is funded by Zarqa University-Jordan.

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