REVISTA DELOS DESARROLLO LOCAL SOSTENIBLE

Reef fish identification through image records using artificial intelligence and convolutional neural network system

Identificação de peixes de recifes através de registros de imagem usando inteligência artificial e sistema de rede neural convolucionário

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ABSTRACT
Coral reef environments show great diversity and abundance of species that represent important biological resources for obtaining food and medicines, in addition to acting as bioindicators of the quality of reef environments, serving as a parameter to diagnose environmental impacts and, simultaneously, to evaluate the availability and use of fishing stocks and biological resources in such environments. Monitoring such ecosystems arises from the urgent need to better understand the natural geographic and environmental variability of these systems, as well as their main drivers of change, to inform and promote more effective management of such environments. With the growing need to monitor communities of reef organisms, particularly fish, the creation of a digital analysis method would make a great contribution to the studies of reef fish. To fill this knowledge gap, our work evaluates the possibility of using an artificial intelligence mechanism using convolutional neural networks (CNN) to identify and count reef fish in image records, to optimize digital analysis of videos and/or photos in reef environments for fish ecology studies. The accuracy of the CNN identification method was effective, although it still has challenges to improve, such as: the need for a preliminary survey of reef fish species existing in the target area to be monitored, with the capture of good resolution images in different positions space for each species; production of an image bank with a large number of diverse images for each species (minimum of 200 images per species) and; To detect fish in videos, fast computers with a dedicated GPU card are needed, especially if the videos are high or ultra-resolution and have a large number of fps.

Keywords: reef fish monitoring, fish identification, fish taxonomy, AI for biological purposes.

RESUMO
Os ambientes de recifes de corais apresentam grande diversidade e abundância de espécies que representam importantes recursos biológicos para obtenção de alimentos e medicamentos, além de atuarem como bioindicadores da qualidade dos ambientes recifais, servindo de parâmetro para diagnosticar impactos ambientais e, simultaneamente, avaliar a disponibilidade e uso de estoques pesqueiros e recursos biológicos nesses ambientes. O monitoramento de tais ecossistemas surge da necessidade urgente de compreender melhor a variabilidade geográfica e ambiental natural destes sistemas, bem como os seus principais fatores de mudança, para informar e promover uma gestão mais eficaz de tais ambientes. Com a crescente necessidade de monitorar comunidades de organismos recifais, particularmente peixes, a criação de um método de análise digital daria uma grande contribuição para os estudos de peixes recifais. Para preencher essa lacuna de conhecimento, nosso trabalho avalia a possibilidade de utilizar um mecanismo de inteligência

artificial utilizando redes neurais convolucionais (CNN) para identificar e contar peixes recifais em registros de imagens, a fim de otimizar a análise digital de vídeos e/ou fotos em ambientes recifais para estudos de ecologia de peixes. A precisão do método de identificação CNN mostrou-se eficaz, embora ainda existam desafios a melhorar, tais como: a necessidade de um levantamento preliminar das espécies de peixes recifais existentes na área alvo a ser monitorada, com a captura de imagens de boa resolução em diferentes posições espaciais para cada espécie; produção de um banco de imagens com grande número de imagens diversas para cada espécie (mínimo de 200 imagens por espécie) e; Para detectar peixes em vídeos, são necessários computadores rápidos com placa GPU dedicada, principalmente se os vídeos forem de alta ou ultra-resolução e tiverem grande número de fps.

Palavras-chave: monitoramento de peixes de recifes, identificação de peixes, taxonomia de peixes, IA para fins biológicos.

1 INTRODUCTION

Coral reef environments exhibit the greatest diversity and abundance of species of living beings of all known marine ecosystems on the planet. Scientists estimate that there may be countless undescribed species living in or around reef environments. In addition to providing various types of food, their biological resources can also be related to the search for new medicines for the 21st century. Many drugs are being developed from reef organisms as possible cures for cancer, arthritis, human bacterial infections, viruses, among other diseases (NOAA, 2022; HEENAN *et al.*, 2017).

Fish have been studied as one of the most important indicators of diversity and biomass of reef environments, serving as a parameter to diagnose environmental impacts and, simultaneously, to assess the availability and use of fish stocks in such environments (MCCLANAHAN, 2019). Such studies become increasingly important, as human impacts on reef environments continue to grow, highlighting global climate change, environmental pollution, overfishing and pressure from urbanization and/or tourism (ATEWEBERHAN et al., 2013).

Thus, there is an urgent need to better understand the geographic and natural environmental variability of these systems, as well as their key drivers of change, to inform and promote more effective management of coral reef ecosystems (HEENAN et al., 2017).

In view of this world-wide picture, the scientific community has initiated efforts to assess and monitor reef fish assemblages. We know that large-scale, long-term monitoring datasets have an important role to play in this process. There is an important challenge to overcome: the definition and implementation of standardized monitoring methods in gradients of oceanographic conditions and at different levels of human impact, which can result in a powerful data resource, which could be used as a tool to better understand the natural variability and differential susceptibility of coral reef ecosystems and their biological and economic resources to local and global factors (HEENAN et al., 2017).

Several visual census techniques are employed, but the results are often unmatched due to differential methodological performance. Although data comparability can promote better assessment of fish populations and, therefore, management of inshore fisheries that are often critically important, so far, no standardization of research method has emerged (CALDWELL et al., 2016). Among the survey methods are visual censuses and stationary or transect video recordings. Although videos are more reliable documents for visual recording, if it is done with quality, the biggest criticism of the method refers to the time required for image analysis. With the growing need to monitor reef fish communities, the creation of a digital analysis method would make a great contribution to reef fish surveys.

2 OBJECTIVES E JUSTIFICATION

Given the above, it is clear the need to establish a faster and more efficient method of analysis for identifying and counting reef fish from underwater image records. In addition, in this work we evaluate the possibility of using an artificial intelligence mechanism using convolutional neural networks to identify and count reef fish in image records, so that we can optimize the digital analysis of videos and/or photos in environments reefs for fish ecology studies.

3 METODOLOGY

The image analysis method is based on an artificial intelligence (AI) mechanism in the training of a Convolutional Neural Network (CNN) system, so that it is possible to identify the trained object in images and videos. For this analysis, we chose to use the YOLO software ("You only look once"), version 4, following the methodology proposed by KATHURIA (2021).

The training was carried out in a virtual machine in the Google Colab environment, where we can use a Linux virtual machine and a GPU processor, which is much faster for this type of activity. In Google Colab there are some limitations, however as we use a small number of images, we had no problems. Each training lasted more than 4 hours of machine use, generating files of 3 different sizes.

For the experimental training, we used, as a reference, one of the most common fish in the oceans, the *Abudefduf saxatilis*, which were obtained from our own image banks and from databases available on websites specialized in the identification of marine fish, such as Fishbase (FROESE & PAULY, 2022). Images varied in animal position, image resolution, and image size.

The structure and position of the mouth, shape of the caudal fin, pigmentation pattern, position, and size of dorsal, pectoral, pelvic and anal fins were used as detection and taxonomic identification characteristics of the fish in training. Detection is understood as the ability of the AI system to perceive the fish in the image, regardless of position, distance or if the image capture of the fish was partial or total.

In the first training stage, we used 95 images, of which 79 were used for training the neural network and 16 for testing. In the second training stage, 75 images were used, 60 of which were used for network training and 15 for testing. Note that with each subsequent training session, the AI “learning” effect is cumulative. Furthermore, in the first training we used images with various sizes, that is, small images with large images, establishing a 416x416 window and using the "best" weight file generated. In the second training, all the images were resized to have the same length (320) and maintaining the "aspect ratio", removing the repetitions and maintaining a window of size 320 x 320. In both we used 2000 interactions in the training of the neural network and a "learning rate" of 0.0013.

We also tested the detection-related species identification capability. In this case, we have inserted test images of the species and families: *Abudefduf saxatilis* (Pomacentridae), *Chromis limbata* (Pomacentridae), *Stegastes variabilis* (Pomacentridae), *Scartella cristata* (Blennidae) and Epinephelus marginatus (Serranidae).

4 RESULTS

In the preliminary stage, despite the limited number of images used in the training, the software was able to detect and identify the fish in most of the images used. The following are examples of fish identification in the images after training.

Figure. 1 – Abudefduf saxatilis before detection.

Source: Own collection - Silva et al. (2022)

Figure. 2 – Abudefduf saxatilis after detection.

Source: Own collection - Silva et al. (2022)

Figure. 3 – Abudefduf saxatilis before detection.

Source: Own collection - Silva et al. (2022)

Figure. 4 – Abudefduf saxatilis after detection.

Source: Own collection - Silva et al. (2022)

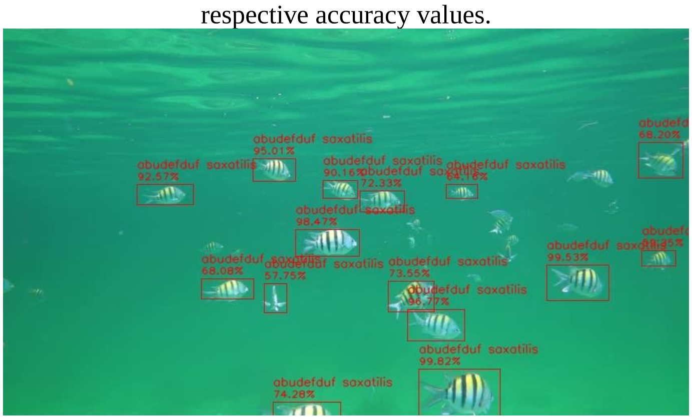
The identification accuracy of the target fish of this study ranged from 69.99% to 99.32%. The accuracy of target fish detection varied as a function of distance, position, degree of fin distention and water transparency.

In the initial training the fish detection showed lower accuracy values than at the end of the training. Even when the image capture of the fish was partial, the AI system was able to detect the fish (Fig. 5). In general, it is noted that the accuracy and detection capacity increase with the position of the fish, with the AI system being more efficient with the fish in lateral profile and at a shorter distance and with clearer water (Figure. 6).

Figure. 5 – Abudefduf saxatilis detection in partial capture (left), with 60.90% accuracy.

Source: Own collection - Silva et al. (2022)

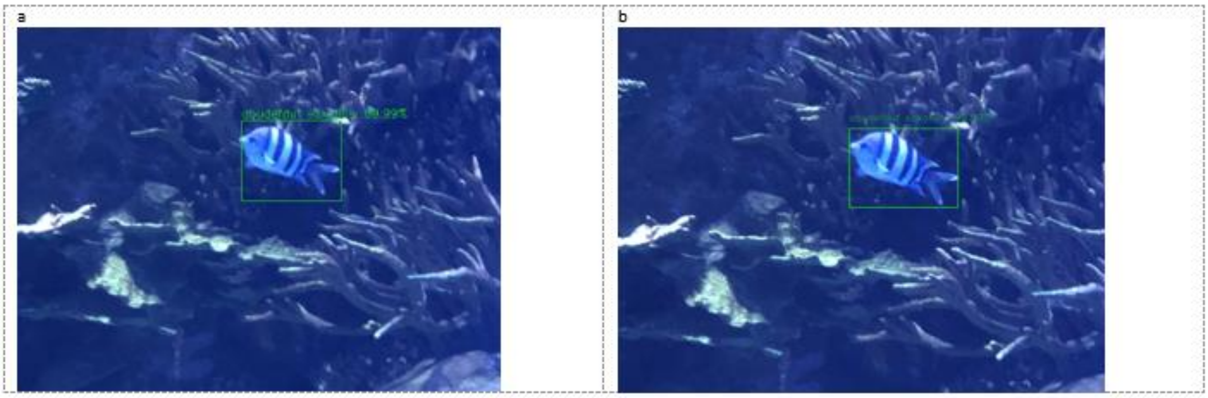
Figure. 6 – Abudefduf saxatilis detection in partial and total capture at different positions and distances and their respective accuracy values.



Source: Own collection - Silva et al. (2022)

On the other hand, as the number of neural network trainings increases, the detection accuracy also increases. Note that after the second training the detection accuracy increased. This can be exemplified by the detection of the image in Figure 7, which compares the detection after the first training (7a) with the detection after the second training (7b). After the first training, the detection accuracy of the specimen was 69.99%, but after the second training, the detection accuracy was increased to 99.89%. This demonstrates that, with a greater number of images for training, the accuracy gradually approaches 100%.

Figure. 7 – Variation of Abudefduf saxatilis detection accuracy after the first training (left – 7a) and after the second training (right – 7b).



Source: Own collection - Silva et al. (2022)

To test the accuracy of identification, we subjected the CNN to different species of fish, after training it for the species *Abudefduf saxatilis*. The results were plotted in a graph (Figure. 8), in which it is possible to verify that the phylogenetically closest species, such as *Chromis limbata* (98.89%) and *Stegastes variabilis* (96.93%), both from the Pomacentridae Family, are more easily detectable as the target species than phylogenetically more distant species such as *Scartella cristata* (46.25%), from the Family Blennidae and *Epinephelus marginatus* (37.83%), from the Family Serranidae.

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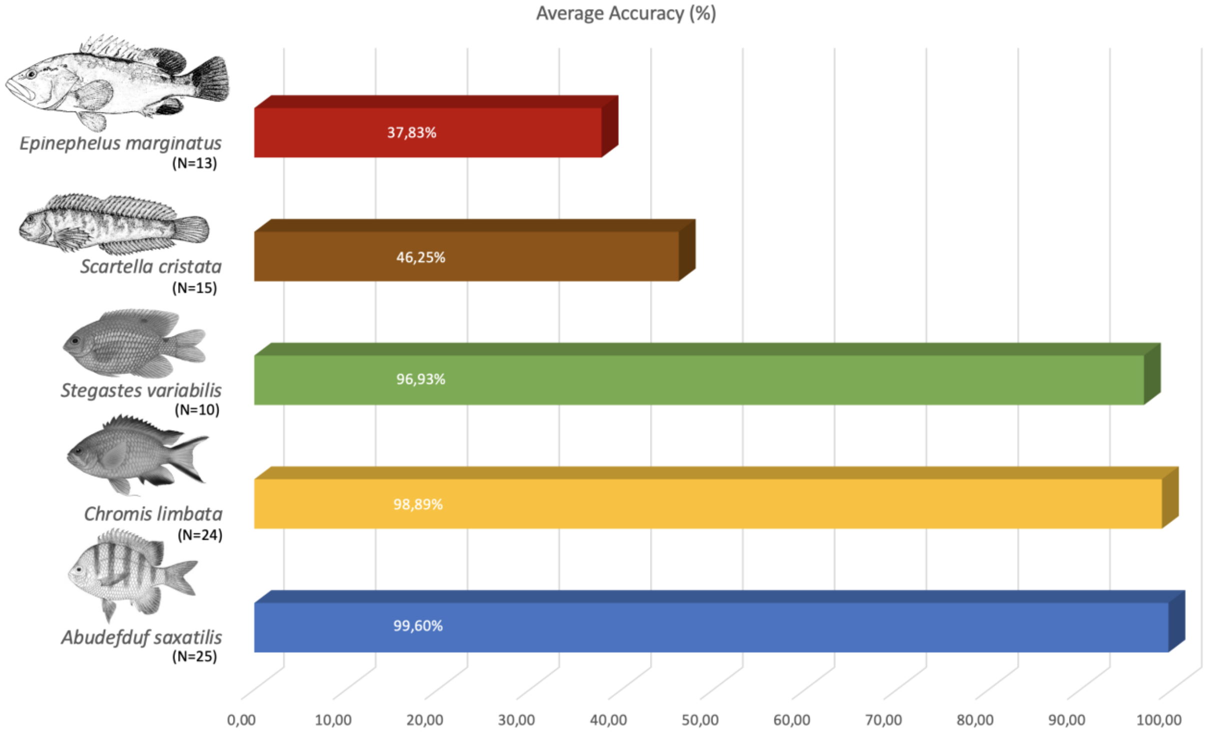
Figure. 8 – Variation in detection accuracy of the different species, based on the second training to identify Abudefduf saxatilis.



Source: Own collection - Silva et al. (2022)

5 DISCUSSION AND CONCLUSION

The accuracy of the identification method by the convolutional neural network system (CNN) was effective, although it still has challenges to improve. Among the limiting factors of the method, we find:

1. The need for a preliminary survey of reef fish species existing in the target area to be monitored, with the capture of good resolution images in different spatial positions for each species. Note that, as the neural network receives the insertion of new images, it learns to detect new species, expanding the detection capacity of the network.
2. The production of an image bank with a large number of diversified images for each species. By our estimates, the desirable number is at least 200 images per species.
3. For the analysis of static images, using neural networks, we can basically use any current computer, however, for the detection of fish in videos, we need fast computers with a dedicated GPU card, especially if the videos are high or ultra-high resolution and with a large number of fps.

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