NEW INSTRUMENTS AND TOOLS FOR SCIENTIFIC EXPLORATION OF SEA AND MARINE FAUNA RECOGNITION

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Abstract

In this work we study the integration of specific hardware, such as tablets with cases for use in the marine environment, and DL algorithms (AI) to permit new methods of marine scientific exploration. The sea tests were carried out in optimal conditions, on the surface or at limited depths of less than 7 metres.

INTRODUCTION

Most life forms evolved initially in marine habitats. By volume, oceans provide about 90% of the living space on the planet. The earliest vertebrates appeared in the form of fish, which live exclusively in water. Some of these evolved into amphibians, which spend portions of their lives in water and portions on land. One group of amphibians evolved into reptiles and mammals and a few subsets of each returned to the ocean as sea snakes, sea turtles, seals, manatees, and whales. Plant forms such as kelp and other algae grow in the water and are the basis for some underwater ecosystems. Plankton forms the general foundation of the ocean animal chain, particularly phytoplankton which are key primary producers.Source

MATERIALS AND MODELS

Dataset

The data set adopted to train the system to recognize marine animals is made up of 24 categories [0, 23] of animals and for each category images of the animal in a marine environment are available as shown in the following table:

Table 1 – Categories of marine animals in dataser

Index	Marine Animal Category	Number of Images
1	Clams	497
2	Corals	500
3	Crabs	499
4	Dolphin	782
5	Eel	497
6	Fish	494
7	Jelly Fish'	845
8	Lobster	499

9	Nudibranchs	500
10	Octopus	562
11	Otter	500
12	Penguin	482
13	Puffers	531
14	Sea Rays'	517
15	Squid	483
16	Sea Urchins	579
17	Seahorse	478
18	Seal	414
19	Sharks	590
20	Shrimp	488
21	Starfish	499
22	Turtle_Tortoise'	1903
23	Whale	572

The total number of photos in the dataset is 13711. By ordering by number of samples of the categories we have that the labels of the categories of the dataset have the following distribution:

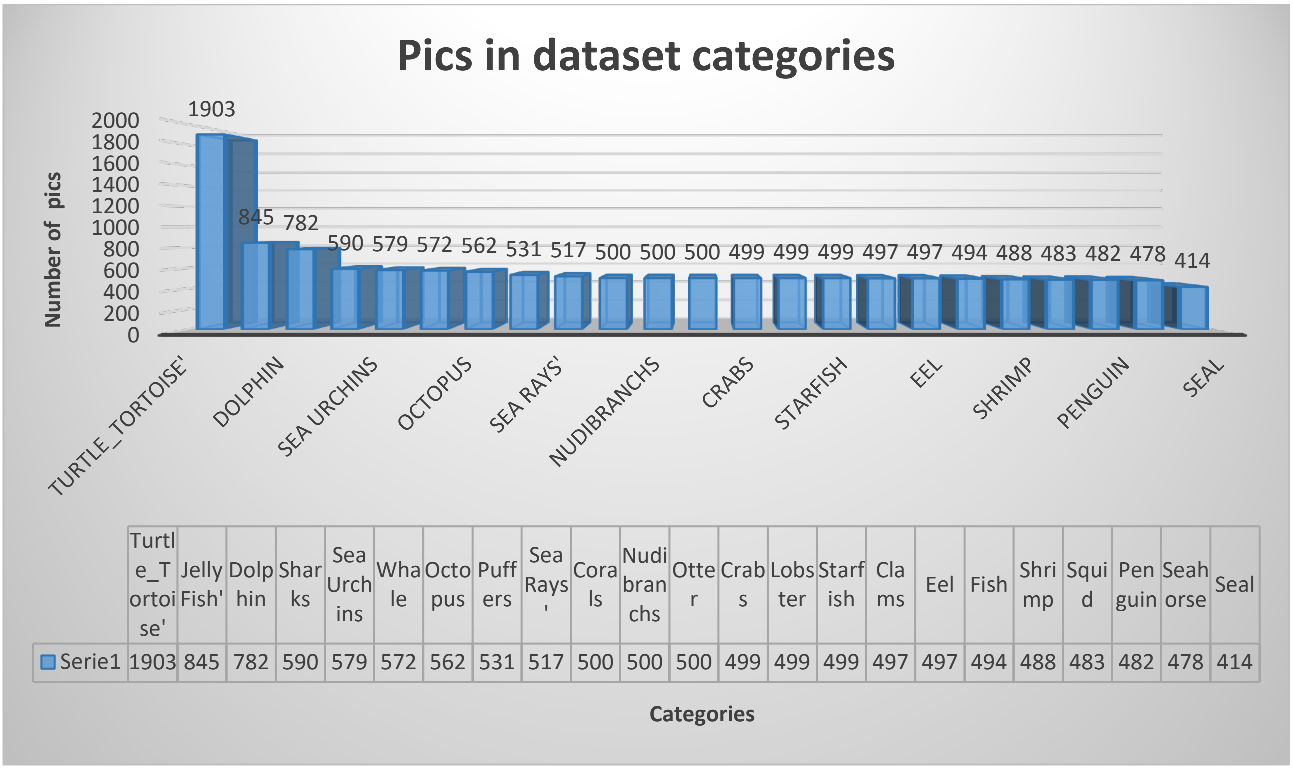

Figure 1 – Ordered distribution of pics number in the categories of animals

Models

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm that can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image, and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. The structure of algoritm of a convolutional Neural network is the following:

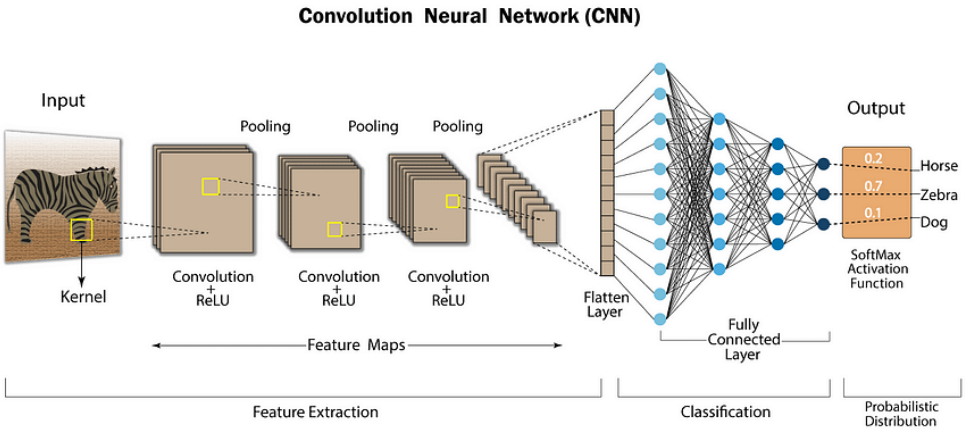

Figure 2 - Convoliutional Meural Network for image recognition [44]

RESULTS AND DISCUSSION

The solution is based on the integration of two components, a tablet with special case for marine use (ALLTAB) which allows the acquisition of photos and videos underwater, and equipped with software for noise reduction and a DL –CNN software which, following training, it allows the recognition of marine animals encountered and photographed or filmed during the scientific mission.

AUGMENTED REALITY DIVE SUPPORT SYSTEM

It consists in a tablet, equipped with a waterproof case and a hybrid system for acoustic localization and inertial navigation, provides "augmented" guidance for divers in marine scenarios, allowing them to have specific information on the marine fauna encountered and framed with the tablet camera.

Figure 3 – Augmented reality dive support system

The system is based on the product of Valtamer, a Finnish technology company, which has developed a waterproof and resistant case of metal and plastic to protect the touchscreen tablet, making them capable of resisting water up to 150 meters deep. Tablets can also support GPS navigation through a cable connected to a receiver with a buoy on the surface. Imaging in water is like driving through fog. There are a lot of particles floating around and scattering the signal. More light doesn't help you see further. To overcome the problems posed by underwater "haze", software from the Norwegian research Institute Sintef was used which allows distinguishing between real signals and background noise. Divers are provided with immediate feedback.

Technical characteristics of ALLTAB adopted:

Table 2 – Technical details of ALLTAB system

Altab® Technical Data	Samsung Galaxy Tab S6 Version SM-T886 (WiFi)
Depth Rating	Pressure tested to 200 m in a wet chamber
Dimensions	L 295 mm, W 205 mm, H 17mm
Weight	2630 g (1130 g in water)
Frame	POM, aluminium

Backplate Front membrane Filling Connectivity USB port Charging	POM, TPU TPU, 1 mm Silicone oil WiFi / Bluetooth Magnetic connector providing USB-A Magnetic connector, max 5 V / 1.4 A
Altab® Technical Details	
Operating System	Android 9.0 (Ple), upgradable to Android 10, One UI 2
Internal memory	128GB 6GB RAM
Cameras	Not available due to inert liquid fill
Display	Super AMOLED capacitive touchscreen, 16M colors; 10.5 inches, 321.9 cm2; 1600 x 2560 pixels
WiFi	802.11 a/b/g/n/ac, dual-band. Wi-Fi Direct
Bluetooth	5.0, A2DP, LE
Sensors	Accelerometer, gyro, proxility, compass
Satellite assisted navigation	A-GPS, GLONASS, BDS, GALILEO
Battery	Non-removabel Li-Po 7040 mAh battery
Battery life	14 hours of usage

MARINE FAUNA RECOGNITION SYSTEM.

It is based on the use of the appropriately split data set to allow the application of Machine Learning methods (training, validation and testing). The data is originally divided into the following clusters:

Data Preprocessing

The data will be split into three different categories: Training, Validation and Testing. The data from the train or training set is used exclusively during the training phase of the CNN model. In the train, therefore, the model learned the relationships between input (our x, the explanatory variables) and output (our y, the target variable, spam/non-spam). To avoid overfitting, and therefore to have real predictive capacity, we give our model data that it has never seen and tell it to make a prediction. This data must necessarily be labeled, i.e. it must contain information on whether the email is spam or not spam. They must be exactly like the ones from train. And this data is part of the Validation Set. Finally, once our model manages to have good performances on the train set and above all on the validation set, we can test our model on other observations (in this case emails) that the model has never seen, observations that are part of the Test Set.

Model Evaluation

The classification machine learning models predicts the probability that each instance belongs to one class or another. It is important to evaluate the performance of the classifications model in order to reliably use these models in production for solving real-world problems. The performance metrics include accuracy, precision, recall, and F1-score

Table 4 – Results of marine animals recognition using CNN and chosen metrics of evaluation

	precision	recall	f1-score	support
Clams	0.604396	0.544554	0.572917	101.000000
Corals	0.460000	0.758242	0.572614	91.000000
Crabs	0.935484	0.956044	0.945652	91.000000
Dolphin	0.729885	0.819355	0.772036	155.000000
Eel	0.761364	0.638095	0.694301	105.000000
Fish	0.728261	0.670000	0.697917	100.000000
Jelly Fish	0.909091	0.982659	0.944444	173.000000
Lobster	0.728155	0.750000	0.738916	100.000000
Nudibranchs	0.694118	0.627660	0.659218	94.000000
Octopus	0.602151	0.470588	0.528302	119.000000
Otter	0.979167	0.979167	0.979167	96.000000
Penguin	0.931818	0.759259	0.836735	108.000000
Puffers	0.876190	0.779661	0.825112	118.000000
Sea Rays	0.817204	0.730769	0.771574	104.000000
Sea Urchins	0.946903	0.981651	0.963964	109.000000
Seahorse	0.721649	0.614035	0.663507	114.000000
Seal	0.822222	0.831461	0.826816	89.000000
Sharks	0.674603	0.787037	0.726496	108.000000
Shrimp	0.462264	0.480392	0.471154	102.000000
Squid	0.673684	0.695652	0.684492	92.000000
Starfish	0.943182	0.965116	0.954023	86.000000
Turtle_Tortoise	0.921053	0.961538	0.940860	364.000000
Whale	0.672727	0.596774	0.632479	124.000000
accuracy	0.777251	0.777251	0.777251	0.777251
macro avg	0.765025	0.755640	0.756639	2743.000000
weighted avg	0.781765	0.777251	0.776235	2743.000000

L'accuratezza totale di riconoscimento è 0.78 ovvero del 78%.

accuracy			0.78	2743
macro avg	0.77	0.76	0.76	2743
weighted avg	0.78	0.78	0.78	2743

Visually the result is that of the following figure:

Figure 4 – Visualization of recognition results using CNN Model

The errors obtained during the recognition phase are highlighted in red. The correct recognitions are shown in green. Trought a classificcation report we canvisualize results achieved in terms of recognitio. It is a summary of the key performance metrics for a classification model, including precision, recall, and F1-score, as well as the overall accuracy of the model. It provides a concise overview of the model's performance, typically broken down by class, and can be used to quickly assess the strengths and weaknesses of the model

Ovviamente questo risultato appare non adeguato ad un uso operativo del sistema per le sperimentazioni acquatiche. Through a technique, denominata, Grad-CAM (Gradient-weighted Class Activation Mapping), we can visualize the regions of an input image that were most relevant for a neural network's prediction. In particular It allows which regions of the image the model focused to make the predicction.

Figure 5 – Grand CAM technique application

We can note that error of prediction in red was caused because the algorithm focused not on Clams but on marine vegetation resembling corals.
To correct this type of errors we deleted from data base all images that were not wel focused on marine animal to recognition. Our dataset was reduced to 10270 pics. After this we had a significant increase in recognition accuracy which becomes 98.7%.
Our aim was not to increase the recognition capacity with artifices, but rather to understand which factors to act on in order to improve the recognition performance and undoubtedly the quality of the photos used for training is one of those.

Test in marine environment
We conducted the recognition tests in a marine environment and the test lasted approximately 30 minutes. The test was conducted on the island of Dino in Praia a Mare (CS) at the beginning of October 2023. The tests took place in snorkeling mode up to a depth of 7 meters, with calm sea and excellent visibility. In the area there are octopuses and fish of various types. We didn't encounter any sharks!!!. In order to be sure we could carry out successful tests, we brought with us an octopus purchased at a fish shop. We positioned it between the rocks so that it could be seen in full or only in part. The system has always recognized this. We then dropped the octopus into the water and the system recognized it. There were also different types of fish present. Again we had excellent performances except for the cases in which the photos were taken from behind the advancing position of solitary fish in the water. Once the test was finished, with the saved photos we used 10 of the 15 unrecognized images (photos of fish taken at the tail end of their wake in the water) and added them to the fish category. This confirms the importance of the training dataset which, together with the marine haze reduction algorithms, can significantly increase the performance of the system. We then carried out the recognition test of the remaining images taken after the fish's trail and obtained full recognition. From this we deduced that the increase in images in our dataset can significantly improve the performance of the system. As the dataset grows, the recognition accuracy performance increases, tending towards 100% accuracy. However, sea visibility conditions can affect the success of recognition.

CONCLUSIONS
The work of integrating specific hardware, such as tablets with cases for use in the marine environment with artificial intelligence algorithms has made it possible to explore new applications for marine scientific exploration. The sea tests were carried out in optimal conditions, on the surface or at limited depths of less than 7 metres. The system proved to be quite effective with a recognition of 93% although during the experimental test phase in water limitations were highlighted which had already characterized the laboratory experimentation, linked to the improvement of the dataset in terms of 1) quantity of images, 2) focusing of the images on the animal to be recognized, 3) representative variety of the dataset, 4) clarity of the water. In the future it will also be necessary to test the system in the dark to simulate conditions of greater depths to make photographic reliefs which without the presence of adeguate sunlight and require the use of the tablet's built-in flash. These further tests will allow us to have reliable data on the use of the system for nocturnal scientific explorations,

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