Universitat de les Illes Balears

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EFFICIENT IMPLEMENTATION OF DEEP NETS FOR VIDEO PROCESSING TO PRESERVE MARINE ECOSYSTEM SERVICES

Miguel Martín Abadal

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Doctoral Programme in Information and Communications Technology

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Doctor by the Universitat de les Illes Balears

Declaration of Authorship

I, Miguel MARTÍN ABADAL, declare that this thesis titled, "Efficient implementation of Deep Nets for video processing to preserve marine ecosystem services" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date:

Supervisor's Agreement

I, Dr. Yolanda González Cid, Ph.D. in Industrial Engineering and Professor at Department of Mathematics and Computer Science, University of the Balearic Islands, attest that:

this dissertation, titled Efficient implementation of Deep Nets for video processing to preserve marine ecosystem services, submitted by Miguel Martín Abadal for obtaining the degree of Doctor in Information and Communication Technologies, was carried out under my supervision and contains enough contributions to be considered a doctoral thesis.

Signed: ______________________________

Date: ______________________________

UNIVERSITY OF THE BALEARIC ISLANDS

Abstract

Higher Polytechnic School
Department of Mathematics and Computer Science

Doctor in Information and Communication Technologies

Efficient implementation of Deep Nets for video processing to preserve marine ecosystem services

by Miguel MARTÍN ABADAL

Marine ecosystems provide multiple services to humans, including provisioning services, such as seafood or fossil energy; regulating services, like coastal protection or water purification; cultural services, as tourism or spiritual benefits; and supporting services, like nutrient cycling or habitat provision.

The provided services are endangered by negative impacts that marine ecosystems are suffering due to multiple causes, some examples of which could be overfishing, habitat destruction, or plastic pollution. Therefore, there exists an urgency to develop new protective measures. One highlighted initiative is to develop scientifically and statistically robust monitoring methodologies and tools to control potential risks or assess the effectiveness of protective and recovery initiatives.

Ocean research and management is facing a new era, led by the technological developments in data collection, allowing the collection of vast amounts of data; and deep learning techniques, capable of processing the data and reducing its processing workload while increasing the spatial and temporal scope of conducted analysis. The marine science community is ready and willing to implement these new tools to a wide range of proposals towards the sustainability of marine ecosystems and its services.

The objective of this thesis is to study the applicability of deep learning solutions, along with computer vision, to develop new tools to preserve marine ecosystems and the offered services. Tools have been developed for three different tasks: *Posidonia oceanica* monitoring, jellyfish quantification and pipeline characterisation. In their development, diverse deep convolutional network model types and architectures have been trained and tested with data gathered from a variety of sources and under different environmental conditions. Additionally, the developed tools have been deployed into diverse platforms and adapted to its features and limitations.

These implementations cover a wide spectrum of scenarios where deep convolutional networks have been applied with good results, automating the data analysis process, expanding the temporal and spatial scope of the analysis or surveys, and improving the repeatability of experiments to detect evolution trends. Thus, validating the proposed methodology to implement deep convolutional networks for video processing to preserve marine ecosystem services.

UNIVERSIDAD DE LAS ISLAS BALEARES

Resumen

Escuela Politécnica Superior
Departamento de Matemáticas e Informática

Doctor en Tecnologías de la Información y las Comunicaciones

Efficient implementation of Deep Nets for video processing to preserve marine ecosystem services

por Miguel MARTÍN ABADAL

Los ecosistemas marinos ofrecen múltiples servicios a los seres humanos, incluyendo servicios de aprovisionamiento como la producción de comida o energía fósil, servicios de regulación como la protección costera o la depuración de aguas, servicios culturales como el turismo o beneficios espirituales y servicios de apoyo como la circulación de nutrientes o la provisión de hábitat.

Estos servicios se ven amenazados por los impactos negativos que están sufriendo los ecosistemas marinos debido a múltiples causas. Algunos ejemplos podrían ser la sobrepesca, la destrucción del hábitat o la contaminación por plásticos. Por lo tanto, existe la urgencia de desarrollar nuevas medidas de protección. Una iniciativa destacada es el desarrollo de metodologías y herramientas de monitoreo científica y estadísticamente sólidas para controlar los potenciales riesgos o evaluar la efectividad de iniciativas de protección y recuperación.

La investigación y gestión de los océanos se enfrenta a una nueva era, liderada por los avances tecnológicos en la obtención de datos, que permiten la recopilación de grandes cantidades de datos; y técnicas de aprendizaje profundo, capaces de procesar los datos y reducir el tiempo de procesamiento a la vez que aumentan el alcance espacial y temporal de los análisis realizados. La comunidad científica marina está lista y dispuesta a implementar estas nuevas herramientas en una amplia gama de propuestas para la sostenibilidad de los ecosistemas marinos y sus servicios.

El objetivo de esta tesis es estudiar la aplicabilidad de soluciones de aprendizaje profundo junto con visión artificial para desarrollar nuevas herramientas con el fin de preservar los ecosistemas marinos y los servicios ofrecidos. Se han desarrollado herramientas para tres tareas diferentes: la monitorización de *Posidonia oceanica*, la cuantificación de medusas y la caracterización de sistemas de tuberías. Durante su desarrollo, se han entrenado y probado diversos tipos de modelos y arquitecturas de redes convolucionales profundas con datos recopilados de una variedad de fuentes y en diferentes condiciones ambientales. Adicionalmente, las herramientas desarrolladas han sido desplegadas en diversas plataformas y adaptadas a sus características y limitaciones.

Estas implementaciones cubren un amplio espectro de escenarios en los que se han aplicado redes convolucionales profundas con buenos resultados, automatizando el proceso de análisis de datos, ampliando el alcance temporal y espacial de los análisis o inspecciones, y mejorando la repetibilidad de los experimentos para detectar tendencias de evolución. Por lo tanto, se ha validado la metodología propuesta para la implementación de redes convolucionales profundas para el análisis de datos en entornos marinos para la preservación de sus ecosistemas y servicios.

UNIVERSITAT DE LES ILLES BALEARS

Resum

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Els ecosistemes marins ofereixen múltiples serveis als humans, incloent serveis d'aprovisionament com la producció de menjar o energia fòssil, serveis de regulació com la protecció costanera o la depuració d'aigües, serveis culturals com el turisme o beneficis espirituals, i serveis de suport com la circulació de nutrients o la provisió d'hàbitat.

Aquests serveis es veuen amenaçats pels impactes negatius que estan patint els ecosistemes marins degut a múltiples causes, alguns exemples podrien ser la sobrepesca, la destrucció de l'hàbitat o la contaminació per plàstics. Així doncs, hi ha la urgència de desenvolupar noves mesures de protecció. Una iniciativa destacada és el desenvolupament de metodologies i eines de monitorització científica i estadísticament sòlides per controlar els riscos potencials o avaluar l'efectivitat d'iniciatives de protecció i recuperació.

La investigació i la gestió dels oceans s'enfronta a una nova era, liderada pels avenços tecnològics en l'obtenció de dades, permetent la recopilació de grans quantitats de dades; i tècniques d'aprenentatge profund, capaces de processar les dades i reduir el temps de processament alhora que augmenten l'abast espacial i temporal dels anàlisis realitzats. La comunitat científica marina està llesta i disposada a implementar aquestes noves eines en una àmplia gamma de propostes per a la sostenibilitat dels ecosistemes marins i els seus serveis.

L´objectiu d´aquesta tesi és estudiar l´aplicabilitat de solucions d´aprenentatge profund juntament amb visió artificial per desenvolupar noves eines per tal de preservar els ecosistemes marins i els serveis oferts. S'han desenvolupat eines per a tres tasques diferents: la monitorització de *Posidonia oceanica*, quantificació de meduses i caracterització de sistemes de canonades. Durant el desenvolupament s'han entrenat i provat diversos tipus de models i arquitectures de xarxes convolucionals profundes amb dades recopilades d'una varietat de fonts i en diferents condicions ambientals. Addicionalment, les eines desenvolupades han estat desplegades en diverses plataformes i adaptades a les seves característiques i limitacions.

Aquestes implementacions cobreixen un ampli espectre d'escenaris on s'han aplicat xarxes convolucionals profundes amb bons resultats, automatitzant el procés d'anàlisi de dades, ampliant l'abast temporal i espacial de les anàlisis o inspeccions i millorant la repetibilitat dels experiments per detectar tendències devolució. Per tant, s'ha validat la metodologia proposta per a la implementació de xarxes convolucionals profundes per a l'anàlisi de dades en entorns marins per preservar els seus ecosistemes i serveis.

Publications

Parts of this thesis have been published in international journals, conference proceedings or as book chapters. Here is a list of all authored or co-authored publications that present relationship with the work developed in this thesis, as well as other publications not directly related to the thesis, but relevant in research.

Additionally, quality indexes are provided for the compendium of journal articles featured in the thesis, to validate its relevance.

Related Publications

Journal Articles

- **Martin-Abadal, Miguel**, Eric Guerrero-Font, Francisco Bonin-Font, and Yolanda Gonzalez-Cid (2018). "Deep Semantic Segmentation in an AUV for Online Posidonia Oceanica Meadows Identification". In: *IEEE Access* 6, pp. 60956–60967. DOI: 10.1109/ACCESS.2018.2875412
  Quality index: JCR2018 *Computer science, information systems*, IF 4.098, Q1 (23/155)

- **Martin-Abadal, Miguel**, Manuel Piñar-Molina, Antoni Martorell-Torres, Gabriel Oliver-Codina, and Yolanda Gonzalez-Cid (2021b). "Underwater Pipe and Valve 3D Recognition Using Deep Learning Segmentation". In: *Journal of Marine Science and Engineering* 9.1. ISSN: 2077-1312. DOI: 10.3390/jmse9010005
  Quality index: JCR2021 *Engineering, marine*, IF 2.744, Q1 (4/16)

- **Martin-Abadal, Miguel**, Gabriel Oliver-Codina, and Yolanda Gonzalez-Cid (2022b). "Real-Time Pipe and Valve Characterisation and Mapping for Autonomous Underwater Intervention Tasks". In: *Sensors* 22.21. ISSN: 1424-8220. DOI: 10.3390/s22218141
  Quality index: JCR2021 *Engineering, electrical & electronic*, IF 3.847, Q2 (95/276)

- **Martin-Abadal, Miguel**, Ana Ruiz-Frau, Hilmar Hinz, and Yolanda Gonzalez-Cid (2020a). "Jellytoring: Real-Time Jellyfish Monitoring Based on Deep Learning Object Detection". In: *Sensors* 20.6. ISSN: 1424-8220. DOI: 10.3390/s20061708
  Quality index: JCR2020 *Engineering, electrical & electronic*, IF 3.735, Q2 (82/273)

- Ana Ruiz-Frau, **Martin-Abadal, Miguel**, Charlotte L. Jennings, Yolanda Gonzalez-Cid, and Hilmar Hinz (2022). "The potential of Jellytoring 2.0 smart tool as a global jellyfish monitoring platform". In: *Ecology and Evolution* 12.11. e9472 ECE-2022-04-00522.R2, e9472. DOI: https://doi.org/10.1002/ece3.9472

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Conference Proceedings

- **Martin-Abadal, Miguel**, Ivan Riutort-Ozcariz, Gabriel Oliver-Codina, and Yolanda Gonzalez-Cid (2019). "A deep learning solution for Posidonia oceanica seafloor habitat multiclass recognition". In: *OCEANS 2019 - Marseille*, pp. 1–7. DOI: 10.1109/OCEANSE.2019.8867304

- Yolanda Gonzalez-Cid, Francisco Bonin-Font, Eric Guerrrero Font, Antoni Martorell Torres, **Abadal, Miguel Martin**, Gabriel Oliver Codina, Hilmar Hinz, Laura Pereda Briones, and Fiona Tomas (2021). "Autonomous Marine Vehicles and CNN: Tech Tools for Posidonia Meadows Monitoring". In: *OCEANS 2021: San Diego – Porto*, pp. 1–8. DOI: 10.23919/OCEANS44145.2021.9705792

- Francisco Bonin-Font, **Abadal, Miguel Martin**, Eric Guerrrero Font, Antoni Martorell Torres, Bo Miquel Nordtfeldt, Julia Maez Crespo, Fiona Tomas, and Yolanda Gonzalez-Cid (2021). "AUVs for Control of Marine Alien Invasive Species". In: *OCEANS 2021: San Diego – Porto*, pp. 1–5. DOI: 10.23919/OCEANS44145.2021.9705915

Book Chapters

- **Martin-Abadal, Miguel**, Ana Ruiz-Frau, Hilmar Hinz, and Yolanda Gonzalez-Cid (2020b). "The Application of Deep Learning in Marine Sciences". In: *Deep Learning: Algorithms and Applications*. Ed. by Witold Pedrycz and Shyi-Ming Chen. Cham: Springer International Publishing, pp. 193–230. ISBN: 978-3-030-31760-7. DOI: 10.1007/978-3-030-31760-7_7

Unrelated Publications

Journal Articles

- Isabel Vidaurre-Gallart, Isabel Fernaud-Espinosa, Nicusor Cosmin-Toader, Lidia Talavera-Martínez, **Martin-Abadal, Miguel**, Ruth Benavides-Piccione, Yolanda Gonzalez-Cid, Luis Pastor, Javier DeFelipe, and Marcos García-Lorenzo (2022). "A Deep Learning-Based Workflow for Dendritic Spine Segmentation". In: *Frontiers in Neuroanatomy* 16. ISSN: 1662-5129. DOI: 10.3389/fnana.2022.817903

Conference Proceedings

- **Miguel Martin-Abadal**, Yolanda González Cid, Joan Roig-Nomura, Jose Jesus Manas, Attila Nagy, Tomas Salom, and Carlos Alonso (2019). "Cloud Type Distinction Based on CNN: An Aid for Short-Term Weather Forecast". In: *Artificial Intelligence Research and Development - Proceedings of the 22nd International Conference of the Catalan Association for Artificial Intelligence, CCIA 2019, Mallorca, Spain, 23-25 October 2019*. Ed. by Jordi Sabater-Mir, Vicenç Torra, Isabel Aguiló, and Manuel González Hidalgo. Vol. 319. Frontiers in Artificial Intelligence and Applications. IOS Press, pp. 152–159. DOI: 10.3233/FAIA190118

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Contents

List of Acronyms

AP	**A**verage **P**recision
ASV	**A**utonomous **S**urface **V**ehicles
AUC	**A**rea **U**nder the **C**urve
AUV	**A**utonomous **U**nderwater **V**ehicles
CNN	**C**onvolutional **N**eural **N**etworks
DBSCAN	**D**ensity-**B**ased **S**patial **C**lustering of **A**pplications with **N**oise
DGCNN	**D**ynamic **G**raph **C**onvolutional **N**eural **N**etwork
DVL	**D**oppler **V**elocity **L**ogger
ESPs	**E**cosystem **S**ervice **P**roviders
FN	**F**alse **N**egatives
FP	**F**alse **P**ositives
IEA	**I**nformation **E**xtraction **A**lgorithm
IMU	**I**nertial **M**easurement **U**nit
IoU	**I**ntersection **o**ver **U**nion
IUA	**I**nformation **U**nification **A**lgorithm
LOS	**L**ine **O**f **S**ight
mAP	**m**ean **A**verage **P**recision
ML	**M**achine **L**earning
nms	**n**on-**m**axima **s**uppression
Po	**P**osidonia **o**ceanica
ROC	**R**eceiver **O**perating **C**haracteristic
ROS	**R**obot **O**perating **S**ystem
ROV	**R**emotely **O**perated **V**ehicles
SVM	**S**upport **V**ector **M**achines
TN	**T**rue **N**egatives
TP	**T**rue **P**ositives
USBL	**S**hort **B**aseline acoustic **L**ink
UVMS	**U**nderwater **V**ehicle **M**anipulator **S**ystems

Chapter 1

Introduction

This chapter first introduces the motivation and context behind this thesis. Next, its main objectives are presented. Finally, it summarises the remaining document structure.

1.1 Context

1.1.1 Ecosystem services

Ecosystem services are the direct and indirect contributions of the natural environment and ecosystems to human well-being. Understanding the interactions between ecological and social systems is a fundamental domain of ecology and is crucial for mapping and managing ecosystem services. This requires an understanding of how ecosystems contribute to human welfare. However, quantifying the management consequences on ecosystem functions and the resulting changes in the value of goods and services depends on the complex interactions between social-ecological systems (Norgaard, 2010).

The "Millennium Ecosystem Assessment" (Hassan et al., 2005) distinguishes between four types of ecosystem services:

- **Provisioning services:** These are material or energy outputs from ecosystems, including food, water, raw materials, and other resources.
- **Regulating services:** These are services that ecosystems provide by acting as regulators, such as regulating the quality of air and soil or controlling floods and diseases.
- **Cultural services:** These are non-material benefits obtained from being in contact with ecosystems, including aesthetic, spiritual, and psychological benefits.
- **Supporting services:** Closely related to regulating services, these services allow the ecosystems to continue providing the other services. They include nutrient cycling, primary production, soil formation, and habitat provision.

As previously mentioned, understanding ecosystem services is a complex task that requires a strong foundation in ecology, including an understanding of the principles and interactions of organisms and the environment Maurer, 2009. The scales at which these entities interact can vary widely, from microbes to landscapes and from milliseconds to millions of years. Furthermore, an ecosystem can provide multiple types of services; for example, the same forest may provide a habitat for organisms, or recreation opportunities and wood for humans. There also exist complex relationships and exchanges of energy and materials between different ecosystems (Bennett, Peterson, and Gordon, 2009).

A suggested research agenda (Kremen, 2005) for the study of ecosystem services includes the following steps:

- Identification of Ecosystem Service Providers (ESPs): species or populations that provide specific ecosystem services and the characterization of their functional roles and relationships.
- Determination of community structure aspects that influence how ESPs function in their natural landscape, such as compensatory responses that stabilize function and non-random extinction sequences that can erode it.
- Assessment of key environmental factors that influence the provision of services.
- Measurement of the spatial and temporal scales on which ESPs and their services operate.

Marine ecosystem services

Marine ecosystems are aquatic environments with high levels of dissolved salt, including deep-sea oceans, estuaries, and coastal marine ecosystems, each of which has unique physical and biological characteristics.

Marine ecosystems are defined by their unique biotic and abiotic components, which support each other for survival. Biotic factors include plants, animals, and microbes; important abiotic factors include the amount of sunlight in the ecosystem, the amount of oxygen, salt, and nutrients dissolved in the water, proximity to land, depth, and temperature.

Marine ecosystem services result from a wide variety of resources that marine ecosystems provide and that are consumed, used, or enjoyed by people (Buonocore et al., 2020; Barbier, 2017; Häyhä and Franzese, 2014). Marine ecosystems provide services of all the previously mentioned types. For example, they provide energy, food, coastal protection, carbon sequestration, and recreational opportunities. Table 1.1 showcases a wide variety of marine ecosystem services.

Provisioning	· Seafood from plants and animals · Renewable and fossil energy · Raw materials · Genetic material · Water
Regulating	· Coastal protection · Carbon sequestration · Climate regulation · Waste treatment · Water purification
Cultural	· Entertainment · Tourism · Aesthetic · Spiritual benefits · Habitat and species value · Cultural heritage
Supporting	· Nutrient cycling · Habitat provision for plants and animals · Gene pool protection

TABLE 1.1: Marine ecosystems services.

These services highly rely on the interplay between biotic and abiotic factors, depending on the physical, chemical, and biological processes that support marine ecosystems. Ecosystem processes include biomass production, organic matter transformation, nutrient cycling, and physical structuring (Strong et al., 2015).

During the last few decades, marine ecosystems have undergone drastic changes at different scales due to multiple anthropogenic causes, including overfishing, eutrophication, invasive alien species, habitat destruction, plastic pollution, and climate change (Ani and Robson, 2021; González-Ortegón and Moreno-Andrés, 2021; Antao et al., 2020; Küpper and Kamenos, 2018). These changes affect the previously mentioned ecosystem processes and thus the biotic and abiotic factors and provided services, affecting human well-being.

There is an urgent need to expand the range of protection for marine ecosystems. Some of the main agencies in the matter, such as the European Environmental Agency (EEA, 2020) or the International Seabed Authority (ISA, 2020), propose diverse measures for the preservation of water and marine environments:

- Progressively develop, implement, and review an adaptive, practical, and technically feasible regulatory framework, based on the best environmental practices, to protect marine ecosystems.
- Conduct assessments to support the implementation and development of regulatory measures.
- Ensure public access to environmental information and facilitate networking for better communication, coordination, and cooperation in terms of data reporting, management, and information sharing.
- Develop scientifically and statistically robust monitoring programs and methodologies to prevent, reduce, or control the potential risk of harmful activities and to assess the effectiveness of any protective or recovery initiatives.

1.1.2 Deep learning

Machine learning is a branch of artificial intelligence and computer science that focuses on the use of data and algorithms to imitate the way humans learn, gradually improving accuracy.

Machine learning powers many aspects of modern society, from web searches and content filtering on social networks to recommendations on e-commerce websites. It is also increasingly present in consumer products, such as televisions or smartphones.

Machine learning systems require the design of a feature extractor that transforms raw input data into an internal representation or feature vector from which a neural network can detect or classify patterns.

Deep learning is a sub-field of machine learning that differs primarily in the fact that deep-learning systems automatically extract features to perform tasks without human intervention from labelled or unlabelled raw data.

Deep learning and neural networks are accelerating progress in areas such as computer vision (Chai et al., 2021), natural language processing (Otter, Medina, and Kalita, 2021), speech recognition (Nassif et al., 2019) or robotics (Morales et al., 2021), among many others.

When it comes to machine or deep learning, there exist diverse categories of models depending on how the learning process is performed:

- **Supervised learning:** For the training procedure, the input is a known training data set with its corresponding labels. The model compares its output with the ground truth label and calculates the difference using a predefined loss function to modify the weights of the neural network. Applications of supervised learning include classification or regression problems.

- **Unsupervised learning:** The models can infer a function to describe previously unknown patterns or hidden structures from unlabeled data, clustering it based on the discovered features. Applications of unsupervised learning include clustering or association problems.

- **Semi-supervised learning:** The models combine a small amount of labelled data with a large amount of unlabeled data, performing weak supervision during training where labelled data acts as sanity checks. These models are able to produce better results than unsupervised learning models without the need of spending resources on labelling the entire dataset.

- **Reinforcement learning:** The models use raw unlabeled data to interact with the environment and are trained on a reward and punishment mechanism, rewarding correct moves and punishing wrong ones. The correctness of an output depends on previous states and outputs, allowing the determination of an ideal behaviour within a specific context to maximize the desired performance. The main applications for reinforcement learning are within complex and variant environments, such as self-driving cars or trading and finances.

Focusing on deep learning, there exists a variety of algorithms that are distinguished by the type of input data, network structure or data processing methods. Although there is no categorical correspondence between tasks to perform and algorithms to use, some algorithms are better suited to perform specific tasks due to their characteristics. Some of the most common deep learning algorithms include Multilayer Perceptrons, Convolutional Neural Networks, Recurrent Neural Networks, Generative Adversarial Networks, Restricted Boltzmann Machines or Autoencoders.

This thesis will focus on the use of Convolutional Neural Networks (CNNs), which are specifically designed for computer vision applications such as classifying images or identifying areas or objects of interest. CNNs applications are numerous and include medical image processing, scene recognition, document analysis, and face or emotion recognition.

CNNs consist of architectures with multiple layers of convolutions that use mask matrices to extract key features from the input data. CNN architectures can be divided into two parts. The first one consists of an encoder, built using multiple convolutional layers along with pooling layers to reduce the input dimensionality. In this section of the architecture, the initial layers produce feature maps containing low-level information such as edges, as the network deepens, it extracts higher-level concepts such as whole objects.

The second part of the network varies depending on the application. For image classification, where no spatial information is needed, the resulting feature maps from the encoder are mapped into a fixed-length vector using fully connected layers, proposing a confidence percentage for each possible class.

On the other hand, for tasks that use spatial information, like the identification of areas or objects of interest, a decoder is built using convolutional and upsampling layers. The low-resolution high-level information of the encoder is transformed into a high-resolution low-level information output. Additionally, skip connections are added, permitting the decoder to access the low-level information from the encoder in order to prevent information loss. Figure 1.1 showcases both CNN types of structures.

There is a wide variety of CNN architectures that can extract different types of information from an image. Following, the most common types of deep CNN architectures, their structures, and their uses are presented.s:

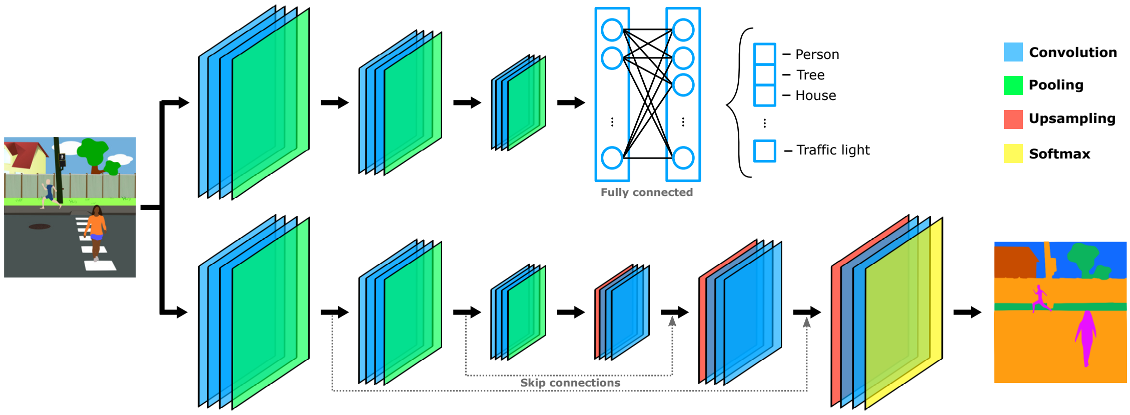

FIGURE 1.1: CNN types of structures. Top: fully connected structure. Bottom: Encoder-Decoder structure.

Image classification CNN architecture

Image classification is the task of categorising images into one or multiple predefined classes. Image classification CNN architectures use a fully connected structure (Figure 1.1) in which spatial information is lost, and a single label is assigned to an entire image. In these architectures, images can be processed quickly and often achieve results that surpass human-level accuracy (He et al., 2015). They are commonly used for simple classification tasks in medical imaging, satellite image processing, traffic control systems, and machine vision.

Object detection CNN architectures

Object detection is the task of identifying the presence of objects in an image and indicating their class and location with a bounding box. Object detection CNN architectures use an encoder-decoder structure (Figure 1.1), maintaining the spatial information needed to detect diverse objects and their position.

Deep learning object detection architectures can be divided into two types, depending on whether they use two-stage or one-stage algorithms (Lohia et al., 2021). Two-stage algorithms use a CNN network to extract image features, then, find possible candidate regions from the feature map using a region proposal network, and finally, perform sliding window operations on candidate regions to determine the object class and position (Girshick, 2015; Ren et al., 2015). One-stage algorithms use a single CNN that performs feature extraction, target classification, and position regression to directly predict the class and position of different targets. One-stage algorithms tend to have lower accuracy than two-stage algorithms but can process images much faster (Redmon et al., 2016; Liu et al., 2016). Object detection applications include autonomous driving, animal detection, medical feature detection, and surveillance.

Semantic segmentation CNN architectures

Semantic segmentation is the task of assigning a label to every pixel in an image, clustering the regions that belong to the same class. Semantic segmentation CNN architectures use an encoder-decoder structure (Figure 1.1) since spatial information is needed.

Deep learning semantic segmentation architectures can also be divided into two groups. Those with region-based algorithms, which use the same methodology of two-stage algorithms described in the Object detection architectures; and those with fully convolutional algorithms, using only a CNN to perform the segmentation task, equivalent to one-stage algorithms. Additionally, a combination of features from object detection and semantic segmentation architectures can be used to perform what is called instance segmentation, where every individual object in an image is detected, classified, and segmented (He et al., 2017; Zhang et al., 2020). Some applications for semantic and instance segmentation include autonomous driving, medical imaging, and document analysis.

Figure 1.2 illustrates the output differences when applying different CNNs architecture types to the same image.

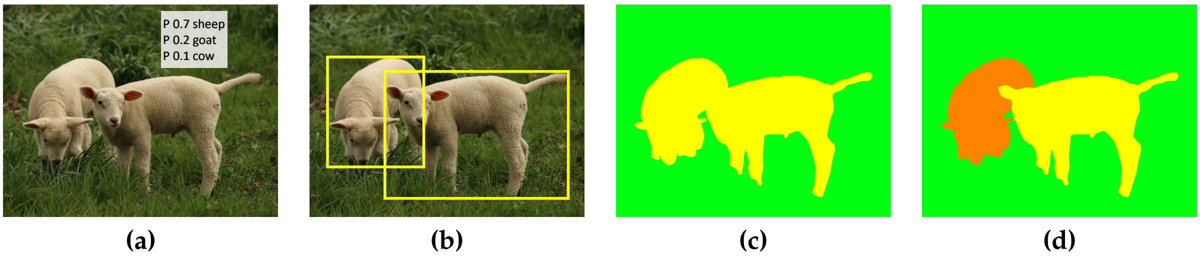

FIGURE 1.2: Output obtained when applying image classification (**a**), object detection (**b**), semantic segmentation (**c**) and instance segmentation (**d**) over the same image.

1.1.3 Deep learning implementation in marine ecosystems

As previously stated, marine ecosystems are diverse and provide multiple resources to the human population. However, anthropogenic factors are negatively impacting these ecosystems, endangering their balance and the services they provide. The scientific community aims to develop new techniques and mechanisms to provide reliable, up-to-date information on the state of marine ecosystems so that management decisions are well-informed.

In recent decades, technological developments in observation and data collection methods have been able to provide lots of information to ecologists. These developments include advances in visual cameras, echosounders, hydrophones, and environmental sensors such as temperature, current or salinity sensors. Concurrently, developments have taken place in the fields of data collection platforms, like underwater stationary observatories, floating buoys or marine vehicles such as Remotely Operated Vehicles (ROV), Autonomous Surface Vehicles (ASV) or Autonomous Underwater Vehicles (AUV). Figure 1.3 showcases different underwater data collection modalities.

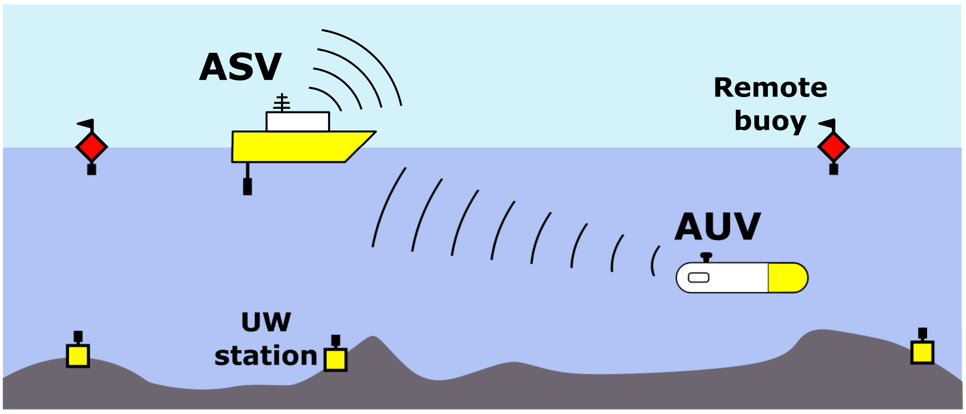

FIGURE 1.3: Examples of underwater data collection modalities.

The combination of these two factors has resulted in exponential growth of gathered information in both temporal and spatial terms, allowing researchers to better study underwater ecosystems and their biotic and abiotic factors (Bacheler et al., 2017). However, the curation and analysis of such vast amounts of data present some drawbacks if manual processing is needed, becoming a tedious and time-consuming task. The implementation of deep learning techniques allows to automate the data processing and reduce the time it takes, enabling the study of long temporal series or large areas and offering extra information to biologists.

Nonetheless, the application of deep learning implementations in marine ecosystems presents diverse challenges. Marine ecosystems are one of the less known ecosystems due to being hard to reach and operate on (Borja, 2014; St. John et al., 2016). Reasons for this include: insufficient oxygen, making it hard to perform manual labour as all procedures must be conducted by divers; high depth-increasing pressure, enforcing that all used data-gathering devices, exploration systems or any other equipment, must be able to function under these conditions; light transmission artefacts related to aquatic mediums that affect the quality of visual data such as light absorption, scattering or flickering; and the uncontrollable and rapid-changing nature of its environment, like variations in water turbidity or currents.

Therefore, despite the previously mentioned advances in data collection methods and platforms, the amount of data available from marine environments is much lower than others. There exist fewer public datasets, meaning that, in most cases, new datasets need to be generated, along with their ground truths. This implies that the size of datasets used to train and test the deep learning networks is usually relatively small, which is a factor to take into account when selecting a network architecture and designing its training.

An important aspect of any implementation is the ability to be executed in real-time, enabling the use of the generated information as input for other systems to make decisions on data collection processes, perform path replanning for exploration tasks, or take immediate action for protection tasks.

Additionally, as communication methods like cable or WiFi are typically unavailable in underwater scenarios, implementations benefit from being deployable and executable directly from the data collection platform without the need for information exchange. Implementations should be efficient and have low computational costs, considering the limited computational power and battery life of these platforms due to the constraints of working in underwater environments.

Monitoring biodiversity

Being able to process large temporal and spatial data is crucial for marine biodiversity monitoring. It allows to better study animal behaviours and early detect growing or declining trends in their numbers, as well as in algae coverage areas or any other important information that can be extracted through CNNs.

A great variety of CNN object detection architectures have been applied to count, measure or log the presence of multiple marine species such as fish and corals on underwater imagery (Li et al., 2015; Villon et al., 2016; Li and Du, 2022; Coro and Bjerregaard Walsh, 2021), whale echolocation clicks on spectrograms (Bermant et al., 2019); or plankton (Dai et al., 2016; Py, Hong, and Zhongzhi, 2016; Li et al., 2021) and algae (Park et al., 2022) on microscopic imagery, among others.

Semantic segmentation architectures are mainly used for extracting information of biodiversity from the benthic zone. In (Alonso et al., 2019) Alonso et al. make use of a semantic architecture along with sparsely labelled data to perform coral segmentation. Mohamed et al. in (Mohamed, Nadaoka, and Nakamura, 2022) use underwater imagery from a towed camera for automated segmentation of benthic habitats using unsupervised algorithms. Other works make use of CNNs to perform a patch-based classification of images containing seagrass meadows and generate a semantic segmentation after merging all patches (Gonzalez-Cid et al., 2017; Burguera, 2020). Finally, some applications make use of satellite imagery, for example, in (Gao et al., 2022), Gao et al. use a modified U-Net architecture to segment floating green algae from optical and SAR images.

Exploration and inspection

The development of ROVs and AUVs into the marine ecosystem has allowed access to deeper ocean regions, to examine larger areas and to operate on more complex underwater scenarios than what was possible with scuba divers. This, along with the usage of CNN to process the obtained information, offers a wide variety of possible implementations for exploration and inspection tasks.

Sonar imagery is widely used when performing exploration tasks, as it can quickly cover large areas while providing good enough resolution. Object detection architectures can be used to detect rather large objects like human bodies (Nguyen, Lee, and Lee, 2020) or warfare mines (Denos et al., 2017), or applied to fields such as archaeology, helping to identify shipwrecks of archaeological sites of interest (Nayak et al., 2021; Character et al., 2021). Semantic segmentation architectures can also be applied to sonar imagery, performing seafloor habitat mapping of a surveyed area and distinguishing the seafloor substratum (Burguera and Bonin-Font, 2020), or to discover new resource areas in deep-sea mineral exploration (Juliani and Juliani, 2021).

For inspection and manipulation tasks, the primary sensing modalities used are vision and laser, which can provide detailed information at short ranges. CNNs can also be applied to the information provided by these sensing modalities to perform underwater inspection and manipulation tasks in different scenarios like offshore oil and gas pipeline networks (Bharti, Lane, and Wang, 2020), metallic surfaces (Chen and Jahanshahi, 2018), or submarine communications cables (Thum et al., 2020).

Environment protection and surveillance

Satellite imagery, along with CNNs, can offer solutions for surveillance purposes such as boat detection to control illegal fishing, ballast water discharge, or anchoring (Kartal and Duman, 2019; Tang et al., 2020).

Segmentation networks can also be applied to satellite images to identify and segment oil spills (Huang et al., 2022; Yang, Singha, and Mayerle, 2022). In underwater imagery, object detection architectures can be used for ghost fishing gear recognition (Politikos et al., 2021) or underwater gas pipeline leak detection (Ahmad et al., 2022).

Additional information on the state of the art of the specific applications later presented in this document can be found in the publications included in their corresponding chapter.

1.2 Objectives

The main objective of this thesis is to develop deep learning-based tools using CNNs for image and video processing and efficiently implement them in real-world scenarios for the preservation of marine ecosystem services. It aims at improving current methods of gathering information by allowing the processing of data for longer periods of time, easing manual labour through the introduction of automatic systems, and increasing the accuracy of detection, annotation, and measuring tasks.

Specifically, this thesis aims to develop and implement tools for three tasks, listed below along with a description of the applications of the tool and specific objectives for each task.

1. ***Posidonia oceanica* monitoring**

Posidonia oceanica is an endemic plant of the Mediterranean sea that plays an important role in the marine and coastal ecosystems (Diaz-Almela and Duarte, 2008). Recent studies have shown a declining trend in its meadows extension (Marba and Duarte, 2010; Telesca et al., 2015). An important part of *Posidonia oceanica* control and recovery comes through monitoring and mapping its meadows, allowing for the early detection of decline trends or assessment of the effectiveness of recovery measures. The specific objectives for this application are:

- Develop a tool able to automatically perform high-precision semantic segmentation of *Posidonia oceanica* meadows and their habitat in sea-floor images, to generate maps and monitor their status.
- Online implementation into Robot Operating System (ROS) middleware (Quigley et al., 2009) to be deployed on AUVs or ASVs to serve as an input to a decision-time adaptive replanning algorithm to dynamically adapt the vehicle exploration path.

2. **Pipeline Characterisation**

There is an increasing need in performing underwater tasks like inspection and intervention on offshore oil and gas rigs or underwater pipeline networks (Yu et al., 2017; Jacobi and Karimanzira, 2013). This has motivated the development of AUVs equipped with sensors and manipulators, allowing to reach deeper and more complex underwater scenarios while reducing the associated risks of such tasks (Ridao et al., 2015; Heshmati-Alamdari et al., 2018). The specific objectives for this application are:

- Design a system able to automatically identify and gather information from valves, pipes, and structural elements on underwater pipeline networks and position them in a 3D space.
- Online implementation into *ROS* middleware to be deployed on AUVs or ASVs providing real-time information for inspection and manipulation tasks.

3. **Jellyfish detection and quantification**

Jellyfish have been recognised as an important part of marine ecosystems, providing multiple benefits to them (Hays, Doyle, and Houghton, 2018; Lamb et al., 2019). Recently, an increase in their numbers has been linked to global change and anthropomorphic causes (Richardson et al., 2009; Brotz et al., 2012), impacting human well-being (Lee et al., 2006; Purcell, Baxter, and Fuentes, 2013; Fenner, Lippmann, and Gershwin, 2010). Jellyfish monitoring efforts are often limited in terms of spatial and temporal coverage, resulting in uncertainty over the species population growth (Pitt et al., 2018). The specific objectives for this application are:

- Develop a tool capable of automatically detecting different species of jellyfish and quantifying their presence over long periods of time.

– Implement the system online to deploy it into a network of buoys to generate real-time logs of jellyfish presence in a studied area.

Another goal of this thesis is to design, test, and validate a methodology for the development and efficient implementation of the previously mentioned tools. The proposed methodology is as follows:

1. Communicate with marine biologists and experts to better understand the problem and discuss possible solutions.
2. Study solutions from a technical viewpoint, accounting for the type of CNN, execution time, accuracy constraints, deployment platforms, etc.
3. Design efficient data collection experiments, marine environments are hard to reach and images can be affected by light transmission artefacts or environmental factors.
4. Collect rich and diverse data to train and test the CNNs on a wide variety of scenarios and environmental conditions.
5. Train and test the selected CNN, fine-tuning its hyperparameters taking into account the study stated in step 2.
6. Develop any post-processing code or algorithms needed to process the network output into useful information.
7. Efficiently implement the developed tool into deploying platforms, taking into account important factors such as computational power, heat dissipation, storage space, and communication networks.
8. Perform tests in real-world scenarios to ensure the tool's applicability and functionality.
9. Provide the necessary software and training to marine biologists and experts so that they can understand and use the developed tools.

1.3 Document Overview

The remainder of this dissertation is organised as follows:

Chapter 2 presents, through the journal article *"Deep Semantic Segmentation in an AUV for Online Posidonia oceanica Meadows Identification"* and conference article *"A deep learning solution for Posidonia oceanica seafloor habitat multiclass recognition"*, the work carried out on *Posidonia oceanica* monitoring, showcasing a deep learning based approach to automatically perform a high-precision semantic segmentation of *Posidonia oceanica* meadows and their habitat.

Chapter 3 covers, through the journal articles *"Underwater Pipe and Valve 3D Recognition Using Deep Learning Segmentation"* and *"Real-time Pipe and Valve Characterisation and Mapping for Autonomous Underwater Intervention Tasks"*, the work carried out on pipe and valve recognition and characterisation, detailing a system based on deep learning that automatically identifies and gathers 3D information from underwater pipeline networks for inspection and manipulation tasks.

Chapter 4 presents, though the journal article *"Jellytoring: Real-Time Jellyfish Monitoring Based on Deep Learning Object Detection"*, the work carried out on jellyfish detection and quantification, showcasing a deep learning tool to automatically log the presence of different species of jellyfish over a video feed.

Chapter 5 highlights the main contributions and discusses the relevance of the research. Finally, proposes diverse possible future lines of research.

Chapter 2

Posidonia oceanica monitoring

This chapter presents the work carried out on *Posidonia oceanica* monitoring.

Posidonia oceanica is an endemic plant of the Mediterranean sea which offers multiple benefits to the marine and coastal ecosystems (Diaz-Almela and Duarte, 2008). Recent studies evidence a significant decline of its meadows on a global scale (Marba and Duarte, 2010; Telesca et al., 2015). An important part of *Posidonia oceanica* control and recovery comes through monitoring and mapping of its meadows and the seafloor habitat where it develops, allowing for early detection of decline trends or assessment of the effectiveness of recovery measures. Currently, these monitoring tasks are mostly carried out by divers (Pizarro et al., 2017), making them slow and costly (Caughlan, 2001; Del Vecchio et al., 2018).

The objective of this work is to automatically perform a high-precision semantic segmentation of *Posidonia oceanica* meadows and their habitat in sea-floor images using deep learning techniques.

The first step was to collect the data to train and test the deep learning architecture. To do so, several hundred images of the seafloor containing *Posidonia oceanica* meadows under different conditions and sediments were collected using an AUV equipped with cameras. Next, a CNN semantic segmentation architecture was implemented and trained several times to obtain the best performing hyperparameters, distinguishing between *Posidonia oceanica* and background. Later, the selected CNN architecture was modified to perform multi-class segmentation, allowing the differentiation of other seafloor substrates such as sand, rocks, *Posidonia oceanica* matte or dead shoots.

The work carried out in this thesis regarding *Posidonia oceanica* habitat recognition is described in detail in two publications. The first one is a journal article explaining the data collection and dataset generation, the semantic segmentation network selection, hyperparameter tuning, validation, and online implementation. The second one is a conference article that presents the multi-class segmentation and validation.

Title: Deep Semantic Segmentation in an AUV for Online Posidonia oceanica Meadows Identification
Authors: **M. Martin-Abadal**, E. Guerrero-Font, F. Bonin-Font and Y. Gonzalez-Cid
Journal: IEEE Access
Published: 11 October 2018
Quality index: JCR2018 *Computer science, information systems*, IF 4.098, Q1 (23/155)

Title: A deep learning solution for Posidonia oceanica seafloor habitat multiclass recognition
Authors: **M. Martin-Abadal**, I. Riutort-Ozcariz, G. Oliver-Codina and Y. Gonzalez-Cid
Congress: IEEE Oceans
Date: 17-20 June 2019
Quality index: GGS Conference rating - B

Chapter 3

Pipeline characterisation

This chapter presents the work carried out on underwater pipe and valve recognition and characterisation.

Over the last few decades, underwater intervention has experienced an uprise due to the increasing need to perform inspection and intervention tasks on industrial infrastructures, such as offshore oil and gas rigs or underwater pipeline networks (Yu et al., 2017; Jacobi and Karimanzira, 2013).

Recently, the usage of Autonomous Underwater Vehicles and manipulators has eased the workload and risks of such interventions, automating these tasks by gathering information from their surroundings, interpreting it and making decisions based on it (Ridao et al., 2015; Heshmati-Alamdari et al., 2018).

The objective of this work is to design an automated system that can identify and gather information on valves, pipes, and structural elements of underwater pipeline networks. Later, the different elements should be positioned in a 3D space to provide information during manipulation tasks and build information maps to accurately depict the layout of a pipeline network.

The first step was to collect point cloud data to train and test a 3D deep learning segmentation architecture. Several hundred point clouds, containing different layouts of underwater pipes and valves, were generated using stereoscopic vision from a pair of cameras mounted on diverse marine vehicles. Following, two deep learning architectures were implemented and tested to find the best performing hyperparameters for pipe and valve segmentation. Finally, algorithms were developed to extract manipulation information from the detected instances, such as pipe vectors, gripping points, the position of structural elements like elbows or connections, and valve type and orientation. Additionally, if point clouds are spatially referenced, an information map of an inspected area can be created.

All work is described in detail in two published journal papers. The first one details the data gathering process and the network selection, training, and evaluation, as well as hyperparameter study in terms of segmentation performance and computational time. The second article presents an upgrade of the used segmentation network and introduces new training and testing data. Additionally, the information extraction and unification algorithms are described and validated. Finally, the article describes the online implementation and execution of the network and algorithms on an AUV, providing real-time information for inspection and manipulation tasks.

Title: Underwater Pipe and Valve 3D Recognition Using Deep Learning Segmentation
Authors: **M. Martin-Abadal**, M. Piñar-Molina, A. Martorell-Torres, G. Oliver-Codina and Y. Gonzalez-Cid
Journal: Journal of Marine Science and Engineering
Published: 23 December 2020
Quality index: JCR2021 *Engineering, marine*, IF 2.744, Q1 (4/16)

Title: Real-time Pipe and Valve Characterisation and Mapping for Autonomous Underwater Intervention Tasks
Authors: **M. Martin-Abadal**, G. Oliver-Codina and Y. Gonzalez-Cid
Journal: Sensors
Published: 24 October 2022
Quality index: JCR2021 *Engineering, electrical & electronic*, IF 3.847, Q2 (95/276)

Chapter 4

Jellyfish detection and quantification

This chapter presents the work carried out on jellyfish control.

Jellyfish have been recognised as an important part of marine ecosystems, providing multiple benefits (Hays, Doyle, and Houghton, 2018; Lamb et al., 2019). Recently, an increase in its numbers has been linked to global change scenarios such as high fishing pressure (Richardson et al., 2009) and global warming (Brotz et al., 2012). This increase can create a multitude of impacts on human wellbeing, such as clogging seawater intake systems in water desalination and power plants (Lee et al., 2006), killing farmed fish in pens (Purcell, Baxter, and Fuentes, 2013) or creating negative impacts on coastal tourism (Fenner, Lippmann, and Gershwin, 2010).

Jellyfish monitoring efforts using underwater video observations tend to have limited spatial and temporal coverage due to human-based data logging approaches ranging from quantitative to presence/absence and relative abundance indices (Condon et al., 2013). The scarcity of consistent long-term temporal and spatial data on jellyfish is such that there is uncertainty about its population growth (Pitt et al., 2018).

The objective of this work is to develop a tool that can automatically detect and quantify different species of jellyfish based on a deep object detection neural network, recording jellyfish presence over long periods.

The first step was to collect the required data. Hundreds of images containing three species of jellyfish were gathered from publicly available videos on diverse social media sites. Next, an object detection CNN architecture was trained, and the best hyperparameters were selected. Then, a quantification algorithm was developed to track jellyfish occurrence on video recordings. Finally, the neural network and quantification algorithms were adapted to be executed online on stationary marine buoys, being able to log the presence of jellyfish in real-time.

This work is presented in detail in a journal article describing the data collection, network and hyperparameter selection and validation, quantification algorithms, and online implementation.

Title: Jellytoring: Real-Time Jellyfish Monitoring Based on Deep Learning Object Detection
Authors: **M. Martin-Abadal**, A. Ruiz-Frau, H. Hinz and Y. Gonzalez-Cid
Journal: Sensors
Published: 19 March 2020
Quality index: JCR2020 *Engineering, electrical & electronic*, IF 3.735, Q2 (82/273)

Chapter 5

Conclusions

This chapter summarises the contributions of this thesis and analyses the research relevance, main findings, and drawn conclusions. Finally, it presents some areas of improvement and possible future lines of research.

5.1 Contributions and discussion

The main objective of this thesis was to develop deep learning-based tools using CNNs for image and video processing and to implement them in real-world scenarios for marine ecosystem services preservation tasks. It also aimed to design, test, and validate a methodology for the development and efficient implementation of these tools.

This thesis presents three different tools, each tackling a specific task with varying requirements. Diverse types of deep CNNs were used, and their applicability was tested across a wide range of scenarios.

Following, the main objectives and contributions for each task are presented. Specific scenarios where CNNs have been implemented are also detailed, discussing the selected CNNs architecture types, data gathering methods, and deployment platforms.

1. ***Posidonia oceanica* monitoring**

The objective was to develop a tool to automatically perform high-precision semantic segmentation of *Posidonia oceanica* meadows and their habitat in sea-floor images using deep learning techniques. The following work was carried out:

- Dataset generation: 483 images containing *Posidonia oceanica* meadows and their habitat were gathered from six immersions conducted on different Mediterranean sea locations at depths ranging from 2-20 meters. The images were taken using multiple cameras mounted on an AUV and under diverse environmental conditions such as sunlight or water turbidity, ensuring robust network training. Additionally, semantic segmentation ground truths were generated.

- CNN implementation: Considering that *Posidonia oceanica* grows in dense meadows of irregular shapes and, equally, sea-floor substrates do not have a defined shape, CNN semantic segmentation architectures were selected as the most adequate approach. These architectures are able to perform pixel-wise classification, distinguishing multiple areas in an image without shape restrictions. The selected network was the VGG16-FCN8 (Simonyan and Zisserman, 2014) and, after selecting the best-performing hyperparameters, it achieved AUC values of 97.7% when performing a binary classification between *Posidonia oceanica* and background, and of 96.8% when distinguishing between *Posidonia oceanica*, rock and sand substratum.

- Deployment: The output layer of the CNN was adapted to reduce the inference time, allowing online execution. Additionally, integration into AUV and ASV platforms was performed using the *ROS* middleware.

This work was developed under the "DEvelopment of new TEChnologies for the automatic and periodic assessment of changes in POSidonia meadows due to anthropogenic causes" (DETECPOS) project (SRV, 2020) and has been used to generate offline *Posidonia oceanica* semantic maps of large areas for its control and monitoring (Gonzalez-Cid et al., 2021). Additionally, it has been deployed in an AUV, performing online image segmentation, serving as an input source to a generation of online semantic coverage maps (Guerrero-Font et al., 2021b) and to a decision-time adaptive replanning algorithm to dynamically adapt the robot exploration using the visual information gathered online (Guerrero, Bonin-Font, and Oliver, 2021).

The generated dataset, trained models, and additional code are provided to the scientific community in (**Martin-Abadal, Miguel**, 2018).

2. **Pipeline Characterisation**

The objective was to design a system able to automatically identify and characterise valves, pipes, and structural elements on underwater pipeline networks and position them in a 3D space to provide information during inspection and manipulation tasks. The following work was carried out:

– Dataset generation: 606 point clouds showcasing a wide variety of pipe structures and valve connections over different backgrounds were gathered. The point clouds were generated from pairs of images provided by different stereo camera rigs mounted on an AUV and an ASV. The images were taken under diverse environmental conditions to ensure robust training. Additionally, 3D semantic segmentation ground truths were generated.

– CNN implementation: Underwater pipeline structures range from simpler ones, like pipelines laid on the seabed covering large distances, to more complex ones, such as the pipe and valve layouts found in oil rigs. In all cases, it is important to analyze and extract 3D information from unknown-shaped objects and calculate sizes, gripping points, lengths, etc. Thus, 3D CNN semantic segmentation architectures were selected as the most adequate approach. These architectures are able to perform pixel-wise classification, distinguishing multiple areas in a point cloud without shape restrictions. The selected network was the Dynamic Graph Convolutional Neural Network (*DGCNN*) (Wang et al., 2019) and, after selecting the best-performing hyperparameters, it reached a pixel-wise segmentation F1-score of 87.2%.

– Information processing: Generation of an information extraction algorithm that clusters the pixel-wise information to an instance level, raising the instance-level segmentation F1-score to 95.4%. This algorithm also draws information from the detected pipes and valves, providing lengths, centre and gripping points, and detecting pipe elbows and connections, with very little positioning error.

– Information processing: Generation of an information unification algorithm that merges the information of diverse point clouds provided by the information extraction algorithm and generates information maps of an inspected area.

– Deployment: Adapt the neural network and information algorithms for online execution and integration into AUV and ASV platforms using *ROS* middleware, for surveying and manipulation tasks.

This work was framed on the "TWIN roBOTs for cooperative underwater intervention missions" (TWINBOT) project (SRV, 2018), which aimed to achieve a step forward beyond the current underwater intervention state of the art and the development of a new kind of I-AUVs, able to work autonomously, alone or in a cooperative way. Currently, the "COOPErative Resident robots for Autonomous ManipulatiOn Subsea" (COOPERAMOS) project (SRV, 2021) has taken its place and aims to use at least three I-AUVs, cooperating to enable complex underwater intervention tasks, such as bulky load transport and cooperative complex structure assembly, in a priori unknown area, including obstacles, with high autonomy. The generated dataset, trained models and additional code are provided to the scientific community in (**Martin-Abadal, Miguel** et al., 2021a; **Martin-Abadal, Miguel**, Oliver-Codina, and Gonzalez-Cid, 2022a).

3. **Jellyfish detection and quantification**

The objective was to develop a tool able to automatically detect and quantify different species of jellyfish and log their presence during long periods of time. The following work was carried out:

– Dataset generation: 842 images containing instances of three different species of jellyfish were gathered. The images were extracted from publicly available videos on diverse social media sites. Additionally, object detection ground truths were generated.

– CNN implementation: Monitoring jellyfish populations and trends requires an effective system capable of identifying the number and species of jellyfish present in an area, enabling temporal quantification. To do so, CNN object detection architectures were selected as the most suitable approach. These architectures can localise and classify different object instances in an image. The selected network was the Inception ResNet v2 (Szegedy, Ioffe, and Vanhoucke, 2016) and, after selecting the best-performing hyperparameters, it reached an F1-score of 95.2% in the jellyfish detection task.

– Information processing: Generation of a quantification algorithm based on windowing techniques to log the presence of jellyfish over video sequences.

– Deployment: Adapt the neural network and quantification algorithm for an online execution, ready for integration into stationary marine buoys equipped with cameras.

This work has generated great interest among biologists. A second implementation of this tool has been developed (Ruiz-Frau et al., 2022), including a larger number of jellyfish species and a division between different oceanic regions, with specifically trained models, considering determined jellyfish species. Furthermore, a web page that will allow uploading images for online jellyfish detection and quantification, while providing extra data to enrich the dataset, is under development (Bustos, 2022). The generated dataset, trained models, and additional code are provided to the scientific community in (**Martin-Abadal, Miguel**, 2020).

These implementations cover a wide spectrum of scenarios where deep CNN have been applied with good results, obtaining high accuracy metrics and even surpassing humans in certain applications. They automate the data analysis process, allowing for temporal and spatial extension of the scope of analysis or surveys, and improve the repeatability of experiments to detect evolution trends. Additionally, all implementations have been, or are ready to be, deployed and executed in real-time on diverse platforms. Finally, they have proved their usefulness, as biologists have used them to obtain information during exploration campaigns, and have been integrated into other scientific works as a source of information. Thus, validating the methodology presented in Section 1.2 and proving the feasibility of implementing deep CNNs in challenging environments like marine environments, where data is often scarce and affected by light transmission artefacts or other environmental factors.

5.2 Future Work

Besides the specific future research lines identified for each presented tool, which are described in the "Conclusion" or "Future Work" sections of their corresponding publications, this thesis has identified several potential lines of future work and points for improvement in the design and implementation of deep learning tools for environmental applications.

- Improve data storage and accessibility with enriched metadata and ground truth annotations. Deep learning architectures need to be trained with lots of data, which sometimes can be scarce or inaccessible. It is important that the community moves towards open-source approaches, facilitating progress in the field.

- Study techniques to increase contact between biologists or environment experts and developers. It is crucial that both parties provide continuous feedback in order to assure a good understanding of the problem and the required system characteristics and features.

- Explore the implementation of semi-supervised or unsupervised deep learning approaches. Data curation and ground truth generation can be a time-consuming and tedious task due to the high volume of required data. These approaches could improve the obtained results and ease the workload, focusing the research on the exploration of new applications or solutions.

- Study the implementation of 3D information in deep learning environmental applications. During the work carried out for pipeline characterisation, the usefulness of working with 3D information was featured. Most CNN applications in the fields of biology and conservation use 2D information, albeit the many benefits 3D information can provide. In object detection and classification, 3D information could be used to identify new features on the studied species or objects, to size them, or to detect their pose. On broader analysis, using semantic segmentation, like seafloor inspection and identification, 3D information could provide the dimensions of a covered area, or even allow to calculate the volume of areas of interest, such as seagrass meadows.

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