### 1.2.4 Machine Learning

Machine learning, a subfield of artificial intelligence (AI), involves the creation of computer systems capable of executing tasks that traditionally require human cognition, such as reasoning, problem-solving, and decision-making (Sarker, 2021). It encompasses the simulation of human-like intelligence in machines, enabling them to identify patterns and make data-driven predictions. The field originated in the mid-20th century, rooted in pattern recognition and the formulation of adaptive algorithms that refine their operations through iterative learning. Early contributions by pioneers such as Alan Turing and Arthur Samuel established the conceptual and practical foundation of the discipline. Alan Turing’s development of the Turing Machine in 1936 represents one of the earliest instances of computational models capable of executing algorithmic processes. The Turing Machine was designed as a theoretical construct to simulate the logic of any computer algorithm, utilizing a tape for memory and a set of rules for operations. While initially intended as a tool for exploring the limits of computation, the principles behind the Turing Machine laid the groundwork for modern machine learning and deep learning (Malekmohamadi Faradonbe et al., 2020). Turing’s emphasis on computation and learning inspired subsequent advancements in artificial intelligence, including the design of systems capable of adaptive and predictive behaviors. Notably, Samuel’s development of a checkers-playing program in the 1950s demonstrated a machine’s ability to improve its performance autonomously through learning processes.

At its core, machine learning involves the development of models—mathematical representations of data relationships—that can identify structures and trends within datasets. These models are trained on data using various techniques. Supervised learning is a method wherein models are trained on labeled datasets, with each input paired to a specific output. This framework enables the algorithm to establish explicit mappings between inputs and their corresponding outcomes. Applications include classification tasks, such as categorizing images or text, and regression, where the objective is to predict continuous variables like temperature or stock prices. The accuracy of supervised models depends significantly on the quality and quantity of labeled data available for training.

Unsupervised learning, on the other hand, functions without labeled data, enabling models to discern patterns or structures inherent in the dataset. It is often applied in clustering, where similar data points are grouped together, and in dimensionality reduction, which simplifies datasets by highlighting their most significant features. This approach is particularly valuable in domains where labeled data is scarce or costly to generate, offering a means to uncover underlying patterns and relationships within complex datasets.

A notable example of supervised machine learning is the Random Forest algorithm, developed by Leo Breiman in 2001 (Breiman, 2001). This learning technique constructs multiple decision trees during training by drawing random subsets of the training data with replacement (a process known as bagging) and selecting a random subset of features at each split. Each tree independently outputs a class prediction (in classification tasks) or a mean prediction (in regression tasks), and the Random Forest aggregates these predictions by majority voting or averaging. This approach enhances the robustness of the model by reducing variance and mitigating overfitting ([Figure 1.15](#fig-learningRates) X). Additionally, Random Forest provides a measure of feature importance, which can be leveraged to identify the most influential variables in a dataset. Random Forest is widely recognized for its robustness, ability to handle high-dimensional data, and resistance to overfitting, making it particularly effective in domains such as remote sensing and bioinformatics. However, the algorithm has its limitations. Random Forest can be computationally intensive, especially with large datasets or a high number of trees, which may increase training time and resource requirements. Additionally, Random Forest can face challenges with highly imbalanced datasets, as it tends to favor the majority class unless specific measures, such as resampling techniques or adjusting class weights, are implemented to address the imbalance effectively. Ensuring a balanced dataset or applying these corrective strategies is crucial for improving the model’s performance in such scenarios (Zhu, 2020). Furthermore, while Random Forest provides feature importance measures, these can sometimes be biased toward variables with more levels or higher variability, potentially misleading the interpretation of results. Finally, the model’s ensemble nature makes it less interpretable compared to simpler models like individual decision trees.

Neural networks, an essential component of deep learning, are inspired by the structure and function of biological neural networks in the human brain (Abiodun et al., 2018). These computational models consist of interconnected nodes, or neurons, organized into layers that process and transform data through weighted connections. Originating in the mid-20th century with early work by researchers such as Warren McCulloch (McCulloch and Pitts, 1943) and Walter Pitts (Pitts, 1943), neural networks initially struggled with computational limitations and theoretical challenges. The development of backpropagation in the 1980s, a method for optimizing weights by minimizing error, marked a significant breakthrough (Werbos, 1974).

Neural networks are particularly novel due to their ability to model complex, non-linear relationships in data (Mienye et al., 2024). They operate through an input layer that receives data, one or more hidden layers that extract features and learn representations, and an output layer that delivers predictions or classifications (Werbos, 1974). Each connection between neurons forms the basis of neural computation, where neurons are the fundamental units inspired by biological nerve cells. In artificial neural networks, a neuron receives input signals, processes them using a mathematical function, and transmits the output to connected neurons. This process is governed by adjustable weights that determine the strength of connections, and an activation function introduces non-linearity, enabling the network to model complex relationships within data. The learning rate, a crucial hyperparameter, dictates how much the model adjusts its weights in response to the error during training. Choosing an appropriate learning rate is essential; a rate that is too high may cause the model to converge erratically or not at all, while a rate that is too low results in slow training and potential stagnation in local minima.

The learning curve, which represents the model’s performance over time, provides critical insights into training dynamics (Figure 1.15). A steep decline in training loss paired with a significant gap between training and validation loss often signals overfitting, where the model memorizes training data but fails to generalize to unseen data. Conversely, a flat learning curve with high training and validation losses indicates underfitting, where the model is too simplistic to capture underlying patterns. Addressing overfitting often involves techniques such as regularization, dropout, and early stopping, whereas underfitting may require enhancing model complexity, increasing data volume, or improving data quality. By carefully monitoring and tuning these aspects, neural networks can achieve robust performance across diverse applications.

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| Figure 1.15: Representation of the impact of Under- Optimal- and Over-fitting on Regression and Classification machine learning models. The bottom row shows a representation of the learning curve of each scenario. |

The primary advantage of neural networks lies in their versatility and performance across a wide range of tasks, from image recognition to natural language processing. They are capable of learning directly from raw data, reducing the need for extensive feature engineering. However, their application is not without limitations (Cheng and Titterington, 1994; Kattenborn et al., 2021; Yuan et al., 2021). Neural networks are computationally intensive, requiring significant processing power and large datasets for effective training. They are also prone to overfitting, especially with small datasets, and their decision-making processes can be opaque, often referred to as the “black box” problem. Despite these challenges, advancements in architectures, such as convolutional and recurrent neural networks, and optimization techniques continue to expand their applicability and effectiveness across domains.

Over the decades, the field has undergone remarkable transformations, driven by increases in computational power, the availability of large datasets, and theoretical advancements. Initially, traditional machine learning methods, such as decision trees and support vector machines, dominated the landscape. However, the past two decades have seen the rise of deep learning, a subset of machine learning characterized by its use of neural networks with multiple layers. This paradigm shift has enabled significant breakthroughs, particularly in areas such as image recognition, natural language processing, and autonomous systems.

The utility of machine learning lies in its adaptability and scalability across disciplines. From enabling predictive analytics in healthcare to enhancing environmental monitoring through RS, machine learning has become an indispensable tool for extracting actionable insights from complex datasets. This section provides a foundation for understanding how machine learning techniques are applied to convert data, such as those obtained through drone mapping, into informative and usable outputs.

### 1.2.5 Remote Sensing applied to Coastal monitoring

Coastal environments represent highly dynamic and sensitive ecosystems shaped by complex interactions between natural processes and human activities. RS technologies are crucial for monitoring these regions, providing detailed data on shoreline erosion, habitat degradation, sediment dynamics, and water quality. High-resolution satellite imagery and drone-based platforms facilitate the detection of fine-scale changes in intertidal zones, mangroves, coral reefs, and other sensitive coastal habitats. These observations enable quantification of spatial and temporal variations, informing evidence-based conservation and sustainable management strategies.

Essential Biodiversity Variables (EBVs) and Essential Ocean Variables (EOVs) constitute a framework for systematically monitoring and understanding ecological and oceanographic changes. Based on the model of Essential Climate Variables (ECVs), EBVs provide a standardized set of biodiversity metrics to detect and analyze changes across spatial and temporal scales (Bojinski et al., 2014; Miloslavich et al., 2018; Pereira et al., 2013). These variables act as an interface between raw ecological data and the biodiversity indicators required for global reporting and policy-making. Similarly, EOVs focus on the biological and ecological characteristics of marine systems, emphasizing metrics such as plankton diversity and biomass, fish populations, and the spatial extent of habitats like coral reefs and seagrass meadows. By standardizing biodiversity and oceanic assessments, EBVs and EOVs enhance consistency and comparability across studies and regions (Muller-Karger et al., 2018, pp. Figure 1.16).

These frameworks address the need for scalable and harmonized observations, aligning with international directives like the Water Framework Directive (WFD, 2000/60/EC) and the Marine Strategy Framework Directive (MSFD), which use habitat diversity as an indicator of aquatic ecosystem health (Borja et al., 2013; E. Papathanasopoulou et al., 2019; Zoffoli et al., 2021). Beyond enabling environmental monitoring, EBVs and EOVs provide a foundation for conservation strategies by addressing knowledge gaps and promoting coordinated action among stakeholders. However, evaluating the ecological status of a large number of water bodies using exclusively field observations turned out to be extremely challenging, and the status of many sites has still not been assessed (Oiry and Barillé, 2021; Papathanasopoulou et al., 2019)

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| Figure 1.16: Current capabilities of remotely sensed data for measuring Essential Biodiversity Variables (EBVs; Pereira et al. (2013)) for soft-bottom intertidal vegetation. Adapted from Muller-Karger et al. (2018). |

Developments in RS have further improved the applicability of EBVs and EOVs (Pereira et al., 2013; Skidmore et al., 2015). Drone and satellite technologies enable large-scale, frequent observations of biodiversity and marine parameters, facilitating the detection of environmental changes. These technologies support tracking habitat extent, species distribution, and functional traits, incorporating these frameworks into conservation policies. The integration of EBVs and EOVs with RS tools advances ecological monitoring and decision-making at local, regional and global scales. However, past and current satellite missions lack optimal technical specifications (spatial, spectral, and temporal resolution) for full operational capability (Muller-Karger et al., 2018). For some habitats, multispectral resolution may be adequate under certain conditions (Zoffoli et al., 2020), although risks of classification errors remain. For others, higher spectral resolution is necessary to distinguish taxonomically distinct groups of vegetation or phytoplankton types (Fyfe, 2003; Launeau et al., 2018; Méléder et al., 2018). Identification relies partly on the presence of spectral absorption bands in the visible associated with photosynthetic and accessory pigments, which can be detected and quantified using high-performance liquid chromatography (Bargain et al., 2013; Jesus et al., 2014; Méléder et al., 2005, 2003a).

## 1.3 Objectives and Overview

Intertidal habitats are particularly complex to map accurately due to their dynamic nature, influenced by tidal cycles, sediment deposition, and erosion processes. The presence of multiple vegetation types interspersed across these habitats further complicates mapping efforts. Several of these vegetation types share similar pigment compositions, including Chla, Chlorophyll-b (Chlb), and accessory carotenoids. This similarity results in spectral signatures that are nearly indistinguishable, complicating their differentiation through RS.

Hyperspectral sensors can detect subtle variations in spectral signatures that are unique to individual vegetation types. These sensors operate by capturing reflectance data across a broad range of wavelengths, enabling the identification of minor differences in spectral patterns. However, multispectral sensors, which record data across fewer and broader wavelength bands, face considerable challenges in distinguishing vegetation types with overlapping spectral features.

Intertidal areas often consist of closely interspersed vegetation types that create mixed spectral signals, a phenomenon known as spectral mixing. This spectral blending occurs when the sensor records reflectance from multiple vegetation types within a single pixel, causing the resulting signature to represent a composite rather than distinct categories. The problem of spectral mixing is further exacerbated as the spatial resolution of the sensor decreases. For instance, Sentinel-2 sensors, with a spatial resolution of 10 meters, are effective only in scenarios where tidal flats are vegetated by a single dominant species. In mixed habitats, this resolution is insufficient to capture smaller patches of vegetation types, which often play a crucial role in biodiversity and ecosystem dynamics.

This limitation has practical implications for the use of remote sensing data in intertidal mapping. The inability to accurately classify vegetation types in mixed habitats reduces the overall effectiveness of such data for ecological monitoring and conservation planning. Smaller vegetation patches, despite their ecological importance, may go undetected, leading to incomplete assessments of habitat distribution and species diversity. These gaps in data can hinder efforts to understand critical ecological interactions, such as nutrient cycling and habitat connectivity, which are often mediated by the spatial distribution of intertidal vegetation. Addressing these challenges requires not only advancements in sensor technology but also the integration of sophisticated classification algorithms capable of disentangling mixed spectral signals.

The application of advanced machine-learning techniques offers a means to enhance the mapping accuracy of sensors with low spatial and/or spectral resolution. These techniques leverage computational algorithms that can identify complex patterns in the data, enabling the differentiation of vegetation types even in challenging spectral conditions. By training these models on sufficiently large and diverse datasets, which include examples from various geographic regions and environmental conditions, they adapt to a wide range of scenarios. This adaptability allows for the creation of robust predictive models capable of handling mixed spectral signals that result from the overlapping vegetation types commonly found in intertidal zones. Furthermore, these algorithms incorporate feature selection and optimization processes to identify the most informative spectral bands, thereby improving classification accuracy. They have demonstrated their utility in generating habitat maps over extensive areas, offering a scalable solution for ecological monitoring.

**The principal objective** of this work is to demonstrate the effectiveness of remote sensing for mapping intertidal habitats and the environmental pressures they face by developing advanced methodologies for accurate vegetation classification and ecosystem monitoring.

This goal will be reached through specific objectives proposed as follow:

* analysing the potential of multispectral spectral sensors for the discrimination of macrophytes from low tide soft-bottom intertidal areas.
* Building an algorithm that discriminates the most common taxonomic classes of vegetation found on soft bottom intertidal sediment.
* Investigate the capacity of remote sensing to monitor intertidal vegetation under abiotic and biotic pressures.

**Chapter 2** establishes the foundation by analyzing a spectral library to assess the feasibility of distinguishing different types of vegetation using RS. It demonstrated that all taxonomic classes could be discriminated, in particular green macroalgae from seagrasses. By employing multi- and hyperspectral datasets, the study identifies the number of spectral bands and specific wavelengths that maximize classification accuracy, showcasing the potential of remote sensing for detailed habitat mapping.

Building upon this result, **Chapter 3** focuses on developing a robust algorithm called DISCOV v1.0, capable of automating the discrimination of green macrophytes in heterogeneous intertidal habitats. Utilizing high-resolution multispectral drone imagery and advanced machine-learning techniques, this chapter addresses the spatial complexity of these environments. The algorithm’s validation across diverse geographic and ecological settings ensures its applicability beyond the initial study sites. This advancement underscores the critical role of cutting-edge RS technologies in ecological monitoring.

In **Chapter 4**, the methodology evolves to include red macroalgae, specifically targeting the invasive species *Gracilaria vermiculophylla*. By updating the algorithm in its v2.0, this study extends its application to a different taxonomic group, demonstrating the flexibility and scalability of the approach. Additionally, this chapter integrates LiDAR-based topographical data to examine the relationship between habitat characteristics and macroalgal distribution. The insights gained from mapping and modeling the spatial dynamics of *G. vermiculophylla* provide valuable implications for managing invasive species and conserving native biodiversity.

**Chapter 5** examines the physiological impacts of environmental stressors, specifically marine and atmospheric heatwaves, on seagrass reflectance. Through controlled laboratory experiments and field observations, this chapter highlights the spectral responses of *Zostera noltei* under heatwave conditions. Well-established spectral indices such as the NDVI and GLI are employed, and a new index, the Seagrass Heat Shock Index (SHSI), is developed to specifically identify heatwave-impacted seagrasses. These indices provide metrics to detect and quantify stress-induced changes. These findings emphasize the role of RS in assessing the resilience and vulnerability of intertidal ecosystems under climate change.

Finally, the **General conclusions and future perspectives** section will close the work, discussing the broader implication of this work and suggesting future directions for research and application. This section will synthesize the key findings from each chapter, highlighting how the advancements in RS methodologies contribute to improved habitat monitoring and management of intertidal ecosystems. It will also emphasize the potential for adapting these approaches to other coastal and marine environments, supporting biodiversity conservation and ecosystem resilience in the face of global environmental changes. Future perspectives will explore opportunities to enhance further RS techniques, such as integrating additional data sources like satellite imagery, and advanced field validation methods. Additionally, potential applications for policy-making, ecosystem restoration, and long-term environmental monitoring will be discussed, emphasizing the critical role of technology in addressing ecological challenges and guiding sustainable coastal management practices.