Optimisation of digital catch monitoring and reporting in European Fisheries

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Executive Summary

The Blue Paper of the OptiFish project offers an overview of monitoring technologies for European fisheries, focusing on automated electronic monitoring (EM), Environmental DNA (eDNA) and sensor fusion systems. It focusses on describing the technologies, their integration into the pilot studies, and key considerations for implementation based on the expertise of the involved partners. Technical specifications, operational guidelines, and user training requirements are described. It also details challenges like accurate catch documentation, real-time data collection, anti-tampering, and fish health monitoring. The document details best practices with emphasis in standardized data formats and protocols for sensor communication to ensure data integrity, alongside strategies for improving data accuracy and responsiveness.

EM systems can provide cost-effective catch data, transparency and help to compliance with regulations. These systems are starting to integrate not only cameras, GPS and sensors data, but also artificial intelligence systems based on image analysis and deep learning (AI-EM, Artificial Intelligence enhanced electronic monitoring systems). Such systems could provide catch quantification by species and sizes and help with estimation of discards and bycatch. Stereo cameras and X-ray imaging might further expand identification capabilities but have higher costs. EM with AI is expected to lead to better data for better management while reducing industry reporting burden. Challenges affecting EM systems include variability in fish appearance, similarities between key species, environmental conditions, operational differences between vessels, overlapping fish or debris obscuring parts of the image. Image quality and variability, impacted by camera resolution, lighting, and dirtiness, significantly affects AI model performance. Biased and imbalance training data complicate the detection of rarer and similar species. OptiFish strategies to improve model reliability include collecting diverse datasets, active learning, synthetic data generation, and domain adaptation.

The eDNA techniques provides a complementary approach for monitoring fish communities and catch compositions. It is a non-invasive method which uses genetic material in the water to estimate fish abundance and biomass. Techniques like eDNA metabarcoding, quantitative PCR (qPCR), and digital PCR (dPCR) enable high-resolution species identification, even for hard-to-detect species. The eDNA has been applied successfully in both bottom trawl and pelagic fisheries for catch compositions and bycatch estimation. It uses passive sampling approaches that does not disrupt fishing operations. However, challenges such as false positives, quantification issues, and eDNA dynamics in water require further research. Combining eDNA with EM systems could enhance species-level estimates complementing each other's weaknesses.

OptiFish integrates AI-EM and eDNA technologies to create a comprehensive monitoring system for European fisheries. Proactive measures, such as instant user notification systems, can alert crews about data quality issues in real-time, minimizing disruptions. Data storage constraints on vessels can be addressed with redundant systems combining onboard and cloud-based storage, while near-real-time image analysis reduces storage demands. Security is paramount, with encryption protocols safeguarding sensitive data during storage and transmission. End-to-end encryption and redundancy in communication infrastructure further mitigate transmission risks, ensuring data integrity and continuity. Data privacy is another significant consideration,

particularly with potential GDPR compliance issues related to identifiable personal data captured on video. Automated masking of sensitive information and anti-tampering measures, such as audit logs and tamper-detection systems, protect data integrity and comply with legal requirements. These combined strategies will ensure reliable, secure, and privacy-compliant data collection for EM systems and eDNA in OptiFish.

Implementing EM and eDNA sampling is challenging due to the diversity in vessel size, design, and layout which are influenced by targeted species and gear types. Large, diverse datasets and non-biased labelling are also required for developing these sampling techniques. Validation requires robust statistical approaches and ground truth built manually by expert and control experiments. The project will evaluate the practicality, adaptability, and effectiveness of these integrated technologies through diverse pilot studies. Each pilot study represents a unique fishing context, incorporating a variety of fishing methods, geographical regions, and catch handling facilities (CHF). The pilot studies include:

1. **CHF Pelagic Pumping:** This pilot tests EM systems in pelagic fisheries targeting species like herring and mackerel. The project explores methods to scale EM data to total catch volumes and assess the feasibility of combining EM with eDNA for improved catch composition estimation.
2. **CHF Sorting Belt:** Conducted on Belgian demersal fishing vessels, this pilot examines the use of multispectral cameras and eDNA for detecting wildlife diseases and assessing the quality of the catch. This technology will enable real-time catch monitoring, optimize fishing operations, and ensure compliance with sustainable practices.
3. **CHF Sorting Table:** This pilot aims to address automated catch documentation on vessels with sorting tables. Due to the diverse layouts and complex catch handling, the pilot will explore the development of mechanical devices to improve image acquisition. The collected data will be integrated with logbook systems to improve transparency and reporting accuracy.
4. **CHF Sorting Deck:** Focusing on Mediterranean and Black Sea demersal trawl vessels, this pilot develops GDPR-compliant EM systems for catch composition, addressing challenges posed by occlusion, large distances from cameras to catch, and varying vessel layouts.
5. **CHF Direct Sorting:** This pilot focuses trust-based self-reporting systems for small-scale fisheries and EM systems for larger vessels. The study will explore the feasibility of these systems, particularly for documenting ETP species, choke species and discards.

Overall, these pilot studies aim to provide real-world evidence of how advanced monitoring technologies can support sustainable fisheries management, facilitate industry reporting, and improve operational efficiencies across different fishing contexts. The outcomes will help guide future technological refinements and inform the development of best practices for the global fisheries sector given the high representativity of these pilots on current vessel types.

Contents

Glossary

Aleatoric Uncertainty	Refers to the inherent randomness or variability in data or a system, often due to natural processes or measurement errors. This type of uncertainty cannot be reduced by further information or analysis and is often present in fields such as environmental monitoring.
Anisakis	A genus of parasitic nematodes (roundworms) that infect marine fish and mammals, often of concern in fisheries and food safety due to their potential to cause human health issues.
Anomalous Events	Activities, occurrences, or behaviours related to fishing operations that deviate from standard, lawful, or ethical practices and potentially indicate illegal, unreported, or unregulated (IUU) fishing, environmental harm, or non-compliance with regulatory frameworks.
Artificial Intelligence (AI)	The use of computer systems that can perform tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and language translation.
Automatic Identification System (AIS)	A maritime communication system used for tracking the movements of ships in real-time, providing data such as vessel identity, position, course, and speed.
Barcode Sequences	Short DNA sequences used for species identification, often derived from genetic markers such as the mitochondrial COI gene, in methods like DNA barcoding.
Benthos	The community of organisms living on or in the bottom sediments of aquatic environments, such as oceans, rivers, and lakes.
Body Masking	A technique used to obscure specific parts of an organism's body, often to protect sensitive data or maintain privacy in images and videos.
Catch Handling Facilities (CHF)	The area onboard fishing vessels where catches are recorded by EM systems. Typically, this is where catches are handled by fishers (divided into species, sorting sizes, and wanted and unwanted catch components), removed from the fishing gears, or where catches are separated from seawater before entering refrigerated seawater tanks.

CatchWAM System	A system developed for fisheries management purposes that employs remote sensing technology to monitor and report (discarded) catch data, enhancing compliance with regulations and improving sustainability.
Class Imbalance	A situation in machine learning where one class or category of data is significantly more frequent than others, potentially leading to biased models that favour the majority class.
Cloud-Based Back-Up	A method of storing data remotely on servers over the internet to ensure its protection, recovery, and accessibility in case of hardware failure or data loss.
Computer Vision	Field of artificial intelligence that focuses on enabling computers to interpret, analyse, and understand visual information from the world around them, such as images and videos.
Control	Regulatory conditions under which the exploitation of the resource may be conducted (FAO, 1994).
CRISPR-Cas Assays	Techniques that utilize the CRISPR-Cas system for gene editing or detecting specific DNA sequences, often used in biotechnology and genetic research. CRISPR-Cas9 is a unique genome editing tool that works by removing, adding or altering sections of the DNA sequence.
Data Annotation	The process of labelling or tagging data (e.g., images, videos, or text) with relevant information to train machine learning models or assist in data analysis.
Data Integrity	The accuracy, consistency, and reliability of data, ensuring it remains unaltered, complete, and trustworthy throughout its lifecycle.
Deep Neural Networks (DNN)	A subset of machine learning algorithms based on artificial neural networks with many layers, used for tasks such as image recognition, speech processing, and more complex predictions.
Delayed	Automatic processing is done at a later time when more computing or manually when manpower is available.
Demersal Fisheries	Fisheries that target organisms living near or on the ocean floor, including species like cod, flatfish, and others, are often caught using bottom-trawling or other methods.
Digital PCR	A method for amplifying and quantifying DNA, used to detect low-abundance targets with high precision and accuracy, particularly useful in environmental DNA studies.

Domain Adaptation	A technique to adjust a model trained on one dataset to perform well on another with different data distributions, improving robustness to variations like lighting, backgrounds, or species.
Edge Computing	A decentralized computing framework that processes data closer to its source rather than relying on centralized cloud servers, reducing latency and bandwidth use.
Electronic Reporting	The digital submission of data or reports, typically in the context of fisheries or environmental monitoring, to ensure timely and accurate data sharing and compliance.
Encryption Protocols	Security measures used to protect data by converting it into a code to prevent unauthorized access, ensuring privacy and data protection during storage or transmission.
Environmental DNA (eDNA)	Genetic material obtained from environmental samples (water, soil, etc.) that can be used to detect the presence of species in an ecosystem without direct observation.
Epistemic Uncertainty	Uncertainty arising from a lack of knowledge or incomplete information about a system, which can potentially be reduced by further data collection or research.
FAO Classification System	A framework developed by the Food and Agriculture Organization (FAO) for categorizing fish species and fisheries based on ecological, biological, and economic factors.
Fishery-Dependent Data	Data collected directly from fishing operations, such as catch data, fishing effort, and vessel-specific information, used to inform fisheries management.
Fisheries Management	The practice of regulating fish stocks and fishing activities to ensure sustainable use of marine resources, balancing ecological health and economic needs.
Fisheries Monitoring	The process of systematically observing and recording fish stocks, fishing efforts, and environmental conditions to inform decision-making in fisheries management.
Fishery-Independent Data	Data collected independently of recreational or commercial fishing activities, such as through surveys or remote sensing, used to assess the health of fish stocks or ecosystem conditions.
Genome Skimming	A technique in genomics that involves sequencing only a portion of the genome to obtain a quick and cost-effective assessment of genetic information.
General Data Protection Regulation (GDPR)	A regulation enacted by the European Union that sets guidelines for the collection, processing, and storage of personal data to ensure privacy and protect individuals' rights.

Graphical User Interfaces (GUIs)	Interfaces that allow users to interact with software or systems visually, using icons, buttons, and other graphical elements, instead of text-based commands.
Hyperspectral Sensors	Sensors that capture a wide range of wavelengths across the electromagnetic spectrum, providing detailed data for applications such as environmental monitoring and remote sensing.
Imagery	The use of images, often captured by cameras or sensors, to analyse, interpret, and monitor various phenomena, particularly in environmental and ecological studies.
Instance Segmentation	A computer vision technique that detects and segments individual objects within an image, differentiating between overlapping objects to identify them separately.
iDPolRAD Algorithm	A method for processing DNA sequence data, often used in ecological studies for species identification and biodiversity monitoring through genetic markers.
IoT Features	(Internet of Things) - Technologies that enable the connection and communication of devices over the internet, allowing for real-time data collection, monitoring, and control in various applications, including environmental and fisheries management.
Joint Bayesian Statistical Model	A statistical modelling approach that combines multiple data sources or assumptions to estimate parameters, often used in fisheries science and environmental monitoring.
Landing Obligation	A European Union regulation requiring fishers to land all caught fish, including unwanted or bycatch species, to reduce waste and promote more sustainable fishing practices.
Machine Learning	A field of artificial intelligence that involves training computer systems to learn and improve from experience without being explicitly programmed, enabling them to identify patterns and make decisions or predictions based on data.
Metabarcoding	A method of DNA barcoding that allows for the identification of multiple species in a sample by sequencing short genetic markers from environmental DNA.
Multispectral Cameras	Cameras capable of capturing data across several specific wavelengths of light, typically used in remote sensing and environmental monitoring.
Monitoring	The ongoing collection and analysis of data to observe and track changes or performance in a system, commonly used in environmental and fisheries management.
Near-Real-Time	A short processing time of usually less than an hour.

Passive Samples (Metaprobes)	Samples collected without direct intervention, often using automated or passive systems for monitoring environmental conditions or species presence.
Process Timing	The speed and timing of the data processing.
Quantitative PCR (qPCR)	A technique used to quantify DNA or RNA in a sample, often applied in environmental DNA studies to measure species presence or genetic material levels.
Raw Electronic Monitoring Data	Data created by EM systems, including the video, images, or other sensor data while a vessel is at-sea, as well as the metadata that provides information about the raw data (e.g., trip sail date, vessel information).
Real-Time	Data is processed as the footage is made with live feedback.
(Remote) Electronic Monitoring	The use of electronic devices and sensors, such as cameras and GPS, to remotely monitor activities on fishing vessels, enabling more accurate data collection and compliance monitoring.
Segment Anything Model (SAM)	A deep learning model designed for general image segmentation tasks, allowing automatic and efficient identification of various objects within visual data.
Self-Sampling Programs	Programs where fishers or stakeholders collect and submit samples for research or monitoring purposes, often used in fisheries management to gather additional data.
Sensor	Devices that detect and measure physical or environmental variables, such as temperature, pressure, or chemical composition, and convert them into signals for further analysis.
Stereo Cameras	Cameras used to capture images in three dimensions, allowing for depth perception and more accurate monitoring in applications such as fisheries and environmental studies.
Synthetic Aperture Radar (SAR)	A remote sensing technology that uses radar waves to capture high-resolution images of the Earth's surface, useful in monitoring environmental changes or maritime activities.
Synthetic Data	Data generated artificially through algorithms or simulations, often used to augment real-world datasets, particularly in machine learning and AI training.
VISTools Platform	A data platform that provides real-time information on catch, fuel consumption, catch effort, …
YOLO (You Only Look Once)	A popular real-time object detection system used in computer vision to identify and locate objects in images or videos quickly and accurately.

List of abbreviations

AI	Artificial intelligence
AI-EM	Artificial Intelligence enhanced electronic monitoring systems)
CHF	Catch Handling Facilities
dPCR	Digital PCR
eDNA	Environmental DNA
EM	Electronic Monitoring
ETPS	Endangered, Threatened, Protected Species
EU	European Union
FPS	Frames per second
IUU	illegal, unreported, or unregulated
PCR	Polymerase chain reaction
qPCR	Quantitative PCR
RSW	Refrigerated Seawater

1. Purpose and Scope of the Blue Paper

This Blue Paper in the OptiFish project serves as a fundamental document that directs the creation and application of monitoring technologies in European fisheries. The blue paper aims to provide a comprehensive overview of existing monitoring technologies to outline the technical specifications and operational guidelines to implement state-of-the-art technologies tailored to a multitude of European fisheries. By outlining the necessary technological specifications, operational guidelines, and user training requirements, the Blue Paper addresses important challenges associated with fisheries monitoring, such as detailing system requirements for accurate documentation of catches, real-time data collection and processing, anti-tampering mechanisms, and fish health monitoring.

The Blue Paper is structured to first present a technological overview of existing and emerging monitoring technologies, such as electronic monitoring (EM), deep learning, eDNA and sensor fusion systems. This overview evaluates the applicability of these technologies across different types of fisheries (i.e., demersal trawl fisheries, pelagic fisheries and artisanal fisheries) and identifies best practices for their adoption. Differences in how catches are handled onboard i.e. sorting bands, sorting tables, direct sorting, pumping, and deck sorting are also discussed.

Following the technology review, the Blue Paper introduces specific technical requirements that are necessary for the efficient use of monitoring technologies. In short, requirements include observation scenes with recommendations for camera position, angles, and distances from target objects to maximize visibility and data accuracy. Camera specifications will detail minimum image resolution, frame rates, and the number of cameras needed to ensure comprehensive coverage of fishing activities. The needs for processing speed and efficiency – in particular, the demand for real-time or near real-time data analysis, including DNA extraction protocols – will be outlined to address processing capacities.

The Blue Paper will use the current standards, and build upon existing systems, and technologies used throughout the European fisheries. It will highlight the importance of standardized data formats to facilitate integration with current systems and databases, as well as protocols for sensor communication to ensure data consistency and integrity across platforms (van Helmond *et al*., 2020). The blue paper will also address considerations related to data quality and the need for reliable data collection in fisheries monitoring. It will explore strategies to improve data accuracy by ensuring that monitoring systems are responsive to potential issues as they arise. This includes mechanisms for providing the crew with timely feedback and guidance to maintain data quality throughout the monitoring process. By outlining such approaches, the Blue Paper aims to enhance operational efficiency and ensure that data integrity is consistently upheld during fisheries operations.

All considerations and minimum requirement specifications outlined in this document serve as inputs for an EM implementation guideline document for European fisheries which is to be provided at the completion of the OptiFish project. Hence, the minimum requirement specifications presented in this Blue Paper, pertains to the specific pilot projects undertaken in OptiFish. As such, the minimum requirement specifications presented in this Blue Paper, are divided into the five pilot projects covering fishing vessels equipped with sorting bands, sorting tables, direct sorting, pumping, and deck sorting.

2. Review of existing monitoring technologies

2.1 Electronic Monitoring

Electronic monitoring (EM) systems have emerged as a tool in fisheries management for increasing access to accurate and comprehensive catch data as well as monitoring fishing activities. They aim to increase transparency of fishing operations and have potential to be used both for improving fisheries management by providing catch data in unprecedented volumes, which can help provide more accurate stocks assessments, and by being used for control and enforcement to ensure legal compliance of fishing activities. Despite their promise, EM technologies face challenges related to scalability, cost, and technical limitations. To overcome these, computer vision and deep learning has shown great promise in automating both catch documentation and fishing event detection.

EM systems are comprised of a combination of both hardware and software. They usually comprise of cameras, GPS sensors, winch rotation sensors, hydraulic sensors which are connected via software through a user interface enabling a variety of analytics to be performed.

The applications of these systems vary. In some cases, they are used for manual video review, where users analyse footage directly. Others incorporate AI-based video processing to automate species identification, quantify catch, or detect specific events on board (Appendix 3) - for instance, the CatchWAM system developed in the EU-funded EVERYFISH project aiming to detect, count, and estimate the weight of discarded catch by species. These systems often include graphical user interfaces (GUIs), either web-based or mobile, to present the processed data. Additional features, such as customized computer vision algorithms, IoT features and vessel monitoring sensors, and satellite communications are also available in certain systems (Table A2.1.). GDPR compliance, achieved through techniques like facial blurring, is another critical feature offered by some providers.

Hardware components used in EM systems can be broadly categorized into two groups: those developed specifically by EM system producers and those can be adapted from general-purpose hardware for use in EM applications. Purpose-built hardware designed to meet the unique requirements of fisheries monitoring often excels in reliability and marine-specific features but can be costly and rigid. Conversely, general-purpose hardware offers adaptability and affordability, albeit with additional customization requirements.

Specialized EM hardware is designed and developed to address the requirements of fisheries monitoring. These devices are often developed with a deep understanding of compliance requirements, stock assessment needs, and operational constraints. This hardware is also developed for flexibility and therefore to meet the monitoring needs of a wide variety of fisheries and vessel types. EM system producers typically focus on hardware capturing high-quality footage while incorporating advanced features such as GPS logging, automated weight recording, and real-time data transmission. The major advantage of these hardware components is the possibility of seamless integration with the software and other hardware of the existing systems of the producers. This enables proactive monitoring in EM systems by improving reliability in marine environments and reducing setup complexities. However, challenges such as higher initial costs, proprietary dependencies, and limited adaptability to other applications highlight the trade-offs inherent in these systems.

In contrast, general-purpose hardware can create alternative monitoring solutions that are tailored to a specific fishery monitoring goal. Hardware such as stereo cameras, edge computers, and advanced sensors have been repurposed to address diverse fisheries data collection needs. For instance, stereo cameras, originally developed for robotics and industrial application are particularly of value for their depth-sensing capabilities. This can enable precise length and volume measurements of fish, a crucial requirement for stock assessments and bycatch monitoring. This can be valuable for monitoring the composition of catch flowing along a conveyor belt or into a discard shoot. However, such a system potentially lacks the ability to provide an overview of the catch handling processes prior to reaching the monitoring location or easily be adapted for alternative catch processing methods.

While general-purpose devices can create bespoke solutions to address specific monitoring needs using widely available components, which can mean lower upfront costs. They may require additional customization to perform reliably in harsh marine environments. Integration with additional systems may also be necessary to create scalable solutions. Such integration can add complexity and cost outside the scope of the particular monitoring goal being addressed.

In the present technology review of EM solutions, we will focus on the hardware and software components associated with collection and processing of visual data. First, we present an overview of EM system providers providing complete EM solutions wrt. obtaining both visual and location data. Hereafter follows a review of existing hardware and software solutions available in EM systems for video data collection, along with details on existing AI models and data availability for developing automated catch reporting and event detection models. The technology review is summarized in Appendix 2 where hardware components (Table A2.1), software components (Table A2.2), available AI models (Table A2.3), annotations tools (Table A2.4), and eDNA approaches (Table A2.5) are listed.

2.1.1 EM system providers

A comprehensive list of available EM system providers suitable for catch reporting, including alternative solutions for small-scale vessels, is provided in Appendix 3. While efforts have been made to include relevant systems, this list may not be complete and will be updated as new systems are identified.

Modern EM systems rely on edge computing platforms to handle the significant volume of data generated by high-resolution cameras and advanced sensors. These platforms are designed to process video and sensor data in real-time, enabling the automation of critical tasks such as species identification, size estimation, and fishing effort monitoring. Please see Appendix XX for an overview of data processing and integration technologies.

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Most EM providers offer cloud-based processing, which serves well for long-term data storage, analysis, and integration. Data that cannot be fully processed onboard, with the use of edge devices equipped with specialized hardware such as GPUs (Graphics Processing Units) or TPUs (Tensor Processing Units), are transmitted to cloud servers, where more computationally intensive operations, such as training machine learning models or conducting in-depth behavioural analyses, can be performed. Cloud processing also facilitates data integration across multiple vessels, enabling the creation of centralized databases that provide a broader perspective on fishing activities and stock health. Cloud platforms offer scalability and allow fisheries stakeholders to access processed data remotely through dashboards and APIs, as is the case for several of the EM providers' solutions.

2.1.2 Hardware

The camera specifications from each of these EM system providers vary – some use self-developed camera systems, whereas others use of-the-shelf monitoring cameras. Some cameras have other parts of the EM system directly integrated, whereas others simply provide video recording capabilities. To get an overview of the different EM camera technologies used by each EM provider, please see Appendix 1. Apart from creating an overview, this appendix also provides a link to the camera specifications offered by each EM provider.

Apart from mono-lens cameras, EM systems can integrate stereo cameras for depth sensing, which is exemplified by several studies and data collection activities in the fisheries research community, including ongoing work from several OptiFish partners. The integration of depth sensing offers significant advantages for size estimation and species classification by adding an additional feature to the objects – but such systems may require calibration for optimal performance in variable lighting or water clarity conditions. Some of the more commonly used stereo cameras in fisheries research are the FRAMOS Industrial Depth Camera D435e (Wageningen) and stereo cameras from the ZED series provided by StereoLabs (ILVO, DTU Aqua). The cameras from FRAMOS and StereoLabs contains similar features important for capturing high-quality videos of fish, herein a global shutter to prevent motion blur.

In addition, advanced sensing solutions, such as X-ray imaging or multispectral cameras, expand the capabilities of EM systems beyond traditional video monitoring.

Similarly, multispectral cameras are useful for assessing fish health and identifying stress indicators, which can be critical for fish welfare and quality, by looking at features beyond those available in traditional red, green, and blue (RGB) images. Spectral imaging allows for more precise wavelengths of light to be imaged, and these wavelengths correspond to various biological and chemical components in the fish. For example, it has been long known that haemoglobin in blood absorbs light at the wavelengths 650 nm differently if it is oxygenated or not. By measuring the reflectance of light at this wavelength and another stable wavelength allows the blood oxygen to be measured, and pulse oximeters use this technique as a cheap and fast way to assess animal health. By combining this with spectral imaging a full map of blood on the fish can be established and relative health measured.

In addition, research has shown other biological markers can be measured by spectral imaging. Quality measurements such as fat content and protein content has been determined in salmon fillets using the infrared region of the spectrum. Whether these techniques could be used on fish that have not been filleted and prepared has not been determined but could be a powerful way to assess fish quality on the line.

While multispectral imaging offers promising opportunities, their higher costs and technical complexity may limit widespread adoption in the near term.

2.1.3 Software

Software components form the operational core of EM systems, enabling the seamless integration of hardware capabilities with user-centric functionalities. These software systems are designed to facilitate the collection, visualization, analysis, and reporting of data critical to sustainable fisheries management. This section explores the landscape of software tools available for EM systems, highlighting their key features, purposes, and contributions to modern fisheries monitoring.

Software components transform this raw data into insights through tools for visualization, management, and reporting. AI-driven technologies, including object detection and segmentation models like YOLO and Mask R-CNN, enhance automation, making processes such as species identification and quantification more efficient. Lightweight models tailored for edge computing allow for real-time onboard processing, minimizing data transmission requirements.

Dedicated Software for EM Systems

EM system producers develop dedicated software tailored to their hardware, ensuring optimal performance and ease of use for end-users. These software solutions are purpose-built to address the unique challenges of fisheries monitoring, incorporating advanced user interfaces that simplify operation and enhance accessibility for diverse stakeholders, including fisheries managers, vessel operators, and regulators.

The software types commonly associated with EM systems can be broadly classified based on their functionality:

6. **Data Visualization and Analysis:** Tools designed to process, analyse, and present EM data in user-friendly formats. These include integrated GIS visualization platforms that map vessel activity, high-resolution data dashboards for real-time monitoring, and annotation tools for species identification and catch quantification.
7. **Hardware Control Software:** Programs responsible for the operation and coordination of EM hardware components. These tools facilitate monitoring of camera feeds, execution of AI models, and diagnostic checks to ensure system functionality.
8. **Catch Reporting Applications:** Electronic logbooks and reporting tools allow fishers to electronically submit detailed catch and effort data. These applications streamline compliance processes and enhance data accuracy by minimizing manual reporting errors.

Functional Purposes and Capabilities

The diverse purposes of EM software reflect the multifaceted demands of modern fisheries management. Key capabilities include:

9. **Integrated Analysis and Visualization:** Sophisticated tools provide real-time, interactive visualizations of fishing vessel data. These systems allow stakeholders to monitor vessel cruise tracks, verify gear deployment times and locations, and confirm records of “kept” and “discarded” catches.
10. **AI-Driven Data Processing:** Software integrated with AI models enables species identification, catch quantification, and annotation of video data, reducing the manual workload and enhancing the speed and accuracy of data analysis.
11. **Operational Management Tools:** Programs that create and manage fishing trips and activities streamline the coordination of fishing operations. These tools support the planning and documentation of fishing activities while enabling the monitoring of gear usage and catch data.

User-Centric Design

The design of EM software reflects a strong emphasis on user-centric functionality. These tools have potential to serve the needs of a diverse user base, including fisheries agencies, the fishing industry, vessel operators, and service providers. Features such as intuitive interfaces, customizable dashboards, and integration with existing management systems enhance usability and promote widespread adoption.

For example, electronic logbook applications offer fishers a straightforward means to record and submit their catch information. These applications are often available as tablet-based systems, ensuring portability and ease of use aboard vessels. Similarly, advanced visualization tools enable managers to assess compliance and environmental impact through interactive maps and dynamic dashboards.

2.1.4 AI Models and Annotation Tools

The integration of AI models and annotation tools into EM systems has revolutionized the processing and analysis of fisheries data. These components play a pivotal role in automating complex tasks, enhancing data accuracy, and providing actionable insights for fisheries management. This subsection explores the key capabilities, applications, and considerations for utilizing state-of-the-art AI models and annotation tools within EM systems.

AI Models in EM Systems

AI models form the backbone of EM data processing, particularly in video analysis. They are indispensable for tasks such as the segmentation of catch items, species identification, and the measurement of catch characteristics. Advanced algorithms, in conjunction with stereo-vision data, enable the generation of segmented masks that are used to determine the length or estimate the weight of individual catches. This granular level of analysis facilitates the automatic extraction of catch composition, providing detailed insights critical for sustainable fisheries management.

State-of-the-art deep learning models are suitable tools for object detection, segmentation, and keypoint analysis in EM applications. Prominent models for these tasks include robust object detection frameworks (Table A2.3) like YOLO-based models, Detectron2, Mask R-CNN, RetinaNet, and Faster R-CNN. These models are widely recognized for their reliability across various scenarios. Additionally, application-specific modifications, such as models optimized for fish detection, further enhance their performance.

Recent advancements, such as the Segment Anything Model v2 (SAMv2) and Mobile SAM, demonstrate exceptional capabilities in segmenting overlapping objects, which is particularly valuable in scenes involving fish in high amounts (Table A2.3). Similarly, keypoint detection models are effective for analysing human activities on fishing vessels, enabling the identification of specific actions or suspicious events, such as the discarding of fish overboard.

Given the operational context of EM systems, where models are often deployed on edge devices in remote locations (e.g., onboard fishing vessels), computational efficiency is a critical factor. Models must be optimized for limited computational resources and energy efficiency without compromising accuracy. Lightweight architectures (Al Muksit *et al.*, 2022) and hardware acceleration techniques are often employed to achieve this balance, enabling real-time processing under constrained conditions.

AI models also contribute to ethical and regulatory compliance in fisheries monitoring. Tools for detecting and automatically blurring human faces ensure adherence to privacy regulations such as the General Data Protection Regulation (GDPR). These features are essential for maintaining the integrity of data collection while respecting the privacy of individuals onboard fishing vessels.

Role of Annotation Tools

Annotation tools complement AI models by facilitating the training and validation of algorithms. These tools enable the creation of high-quality labelled datasets, ensuring that models are robust and generalizable across diverse operational scenarios. They enable efficient labelling of images, video frames, and other modalities, ensuring high-quality datasets for deep learning experiments.

The latest generation of annotation tools integrates AI-aided proposals, which generate preliminary object masks for user approval or refinement. This significantly reduces manual effort while maintaining annotation accuracy. While earlier tools primarily focused on image and video annotations, modern platforms now accommodate diverse data types, including audio, LiDAR, text, and volumetric data. This versatility reflects the expanding applications of AI in fisheries monitoring and beyond.

Annotation tools (Table A2.4) are also evolving in their accessibility and deployment. Cloud-based platforms, which operate directly through web browsers, have become increasingly popular due to their ability to eliminate the need for local installations and enable collaborative workflows across distributed teams. However, these systems are typically paid (i.e., not free-to-use) and require users to upload data to external servers. For datasets that are highly sensitive or valuable, this requirement may pose privacy or security concerns, leading users to prefer alternatives. In such cases, traditional locally installed tools remain a critical option, offering greater control over data storage and processing. These tools are particularly advantageous when handling large datasets or working in environments with limited internet connectivity, underscoring their continued relevance despite the rise of cloud-based solutions.

2.1.5 Challenges in EM Data Collection

Automated EM on fishing vessels can encounter many sources of uncertainty, stemming from both the environment and operational practices that challenge the generalization of the AI models (Kootstra 2024). These uncertainties are tied to different types of variation in the data – ranging from the specifics of the vessel itself to the natural variation in the appearance and composition of the catch. Below, we describe how such variation can arise, and how each can pose challenges to reliable data collection and analysis.

Challenges related to variations and occlusions:

12. **Object Variation:** Variations within EM images arise from the natural diversity found within and across fish species, as well as the debris and benthos that ends up on the conveyor. Even within a single species, fish can vary widely in colour, size, shape, and condition. Catch composition can vary widely between vessels as a result of fishing location, season, and fishing gear type.
13. **Environmental Variation:** Environmental variation is driven by differences between vessels and their on-deck conditions. Conveyor belt designs can vary by colour, texture, speed, and width, each altering the background against which fish appear. Variation in conveyor belt configuration can also complicate hardware integration of EM systems. Some decks may be enclosed while others may be exposed, resulting in lighting and weather-related challenges. These factors mean that an EM system designed for one vessel may perform poorly on another unless these cross-domain discrepancies are accounted for.
14. **Operational variation:** Each vessel has distinct operational procedures that influences the data gathered. For instance, some crews may wash the conveyor or rinse the catch regularly, while others may not, causing variation in how the catch appears on camera. Conveyor belt speed can also vary between vessels, which in turn affects required lighting and camera exposure time or acquisition mode.
15. **Task Variation:** The specific goals of an EM system can also alter data requirements. If the objective is to simply count fish, label requirements are minimal and consistent across vessels. However, downstream tasks such as classification, length/weight estimation, or quality assessment require different and more detailed annotations, and possibly different sensor modalities. Each layer of task complexity requires new types of annotated data.
16. **Occlusion:** Occlusions occur when fish overlap one another or debris and benthos obscures part of the scene, leading to missing information in captured images. This missing information introduces significant uncertainty into annotation and model predictions (Van Essen, 2020). Different fishing gear types and catch-handling procedures (operational variation) can result in varying levels of occlusion between vessels. This complicates annotation of data as well as fish detection, classification, and downstream tasks. Overcoming occlusions may require some preprocessing of the catch (e.g. spreading out a large pile on the conveyor manually).

Challenges related to the data:

17. **Image Quality:** Poor image quality significantly hampers training and use of deep learning models for fish detection. Camera resolution, layout, acquisition modality, and dirtiness impact data usability. Resolution depends on camera type and distance from the target, while layouts influence field-of-view coverage and environmental occlusions. Light conditions, crucial for image sharpness, contrast, and noise levels, depend heavily on the presence, intensity, and angle of light sources. Dirtiness—from water spots, dust, or salt residue—can further degrade image quality, requiring regular cleaning protocols or software for blur detection. The required minimal image quality is task and fisheries dependent.
18. **Class imbalance:** Fisheries often target a few specific species, which will make up the bulk of the catch, while many other (potentially important) species appear infrequently. As a result, datasets can become heavily skewed towards the most common species, causing models to struggle on cases of more rare species. Accurate detection of infrequent classes requires measures to ensure they are sufficiently represented in the dataset. In addition, evaluation metrics used need to be sensitive to class imbalance.
19. **Labelling quality:** Although we strive to annotate the image data without errors, in practice, the quality of the image annotations can differ depending on the quality of the images, the occlusions, the distinctiveness between fish species, and the experience/expertise of the annotator. Labelling errors will influence the performance of the trained models.
20. **Data sharing:** Effective model training requires large, balanced datasets with sufficient variation. Issues such as limited sample size, class imbalance, and inconsistent availability constrain the generalization of DNNs. Proper metadata—including acquisition information, timestamps, and location data (e.g., GPS)—is critical for data reusability and standardization across projects. Additionally, establishing conventions for data annotation, such as FAO classification systems, facilitates consistency and sharing.
21. **Data availability:** Gathering sufficient data with high quality and consistent labelling conventions is a non-trivial, time-consuming and costly endeavour. Capturing the broad range of variation in target objects and environments across vessels, gear types, seasons, and fishing locations demands significant effort in collection and annotation of data. While annotating fish instances can be done by non-experts, classifying species accurately requires expert knowledge and can be costly. How much data is "enough" depends on the complexity of the tasks (relating to the amount of variation and occlusion) and the desired confidence in model accuracy.

Research directions to improve generalization

22. **Collection of rich datasets:** A good performance can be ensured if the distribution of the training data covers the run-time distribution. To address generalization towards the above-mentioned variability, large and diverse datasets covering all practical scenarios are essential for robust model training (Ruigrok *et al*., 2023).

23. **Active learning:** Annotating images is the most time-consuming aspect of data collection. It is therefore important to annotate those images that are most relevant for model training.

Active learning addresses this by selecting those images that the model is most uncertain about for annotation. This results in improved performance using smaller datasets (Blok *et al.* 2022, Sokolova *et al.* review).

24. **Self-supervised learning**: This allows pre-training of deep neural networks on unannotated data. Methods like contrastive learning have been shown to benefit detection models, for instance, in the domain of weed detection (Saleu *et al.* 2024).

25. **Synthetic data:** As described in Section 2.1.6, synthetic data can be used to extend the training sets. These can be based on 3D simulation models, or on modifications of real images. To bridge the sim-to-reality gap, typically a (smaller) set of real training data is needed to fine-tune the networks. This procedure was successfully applied in other agricultural tasks (Barth *et al.* 2018, 2019).

26. **Domain adaptation:** Methods for domain adaptation aim to improve generalization by closing the domain shift between a source and target domain (Zhou *et al.* 2022). This can be used to close the domain gap between the training distribution and run-time distribution (Barth *et al.* 2020).

27. **Uncertainty in Predictions:** Automated systems must provide reliable confidence estimates for predictions (Lamping *et al.* 2023). Two types of uncertainty influence model performance: aleatoric uncertainty (related to data variability) and epistemic uncertainty (arising from model limitations) (Gal, 2016; Kendall & Gal, 2017; Hullermeier & Waegeman, 2012). Addressing epistemic uncertainty is particularly useful for active learning strategies, where uncertain samples can guide further labelling efforts (Valdenegro-Toro & Saromo, 2022).

By addressing these challenges—ranging from data variability and image quality to metadata management and predictive uncertainty—electronic monitoring systems can be significantly improved, ensuring more accurate, scalable, and cost-effective monitoring of fisheries.

2.1.6 Synthetic data

Synthetic data has the potential to be utilized in the OptiFish project, particularly in training AI models aimed at enhancing onboard monitoring of catch volumes and fish health. Although this technology is still under development and its implementation timeline remains uncertain, its inclusion in the blue paper is warranted due to the potential advantages it offers for the project's objectives.

One of the primary benefits of synthetic data is the ability to generate diverse training datasets without the need for extensive fieldwork, reducing the dependency on in situ data collection (Allken *et al*., 2019). By using synthetic data, it becomes feasible to simulate a wide range of real-world scenarios, thereby ensuring more comprehensive model training (Man & Chahl, 2022). This is particularly relevant for fisheries, where conditions on vessels vary significantly depending on factors such as the layout of the vessel, species composition, and environmental variables.

The process of creating synthetic data begins with the development of 3D models, which can then be used to generate image datasets (Wong *et al*., 2019). Once these models are in place, the generation of synthetic data becomes relatively cost-effective. Additionally, synthetic datasets offer the advantage of automated labelling, which not only minimizes manual effort but also ensures consistency and precision.

In the context of OptiFish, the generation of synthetic images of fish presents a valuable opportunity for enhancing AI-driven systems (Allken *et al*., 2021), though it is not without its challenges. Developing realistic synthetic images involves complex 3D modelling, as fish exhibit reflective surfaces and dynamic shapes that must be accurately represented in various conditions. The models need to account for deformations depending on the underlying surface and the interaction with other environmental factors. Furthermore, it is crucial to ensure sufficient variability both within species and across different species, reflecting the natural diversity seen in fisheries.

2.2 Environmental DNA

The analysis of environmental DNA (i.e., genetic material released by organisms into the environment) has proven to be a cost-effective, reliable and non-invasive method to monitor fish communities (Cornelis *et al*., 2024, Dukan *et al*., 2024), assess catch compositions (e.g., Afzali *et al*., 2021, Deiner *et al*., 2021, Miya *et al*., 2022) and estimate the abundance and biomass of commercial catches (e.g., Guri *et al*., 2024, Maiello *et al*., 2022, Maes *et al*., 2023, Maggini *et al*., 2024, Urban *et al*., 2022). Common approaches to obtain eDNA data are eDNA metabarcoding and quantitative (qPCR) or digital PCR (dPCR). Metabarcoding is the simultaneous identification of various taxa using the DNA extracted from an environmental sample (e.g., seawater). Metabarcoding involves the amplification and sequencing of a specific genetic region (also referred to as barcode, for example cytochrome c oxidase subunit I, 12S ribosomal DNA depending on the taxonomic group of interest) which is compared to barcode sequences in a reference database for taxonomic assignment, often at the species-level. Quantitative or digital PCR uses species-specific primers and molecular probes to quantify DNA from target species. High-quality and reliable genetic reference sequences of target and closely related species is required for the development of these species-specific assays (Wu *et al*., 2022).(

In contrast to qPCR and dPCR, eDNA metabarcoding data could not be used to infer absolute species DNA abundances. Guri *et al*. 2024, however, demonstrated the quantitative potential of metabarcoding data using a joint Bayesian statistical model of eDNA and traditional trawl-catch data. Both methods have been effectively applied in a fisheries context to estimate catch compositions and target species abundances (e.g., Guri *et al*., 2024; Urban *et al*., 2022; Maes *et al*. 2023), with new techniques like genome skimming (Hoban *et al*., 2022) and CRISPR-Cas assays emerging (Deiner, 2021).

In bottom trawl fisheries, eDNA metabarcoding has been used to estimate the catch composition on commercial vessels using passive samplers, also referred to as metaprobes, attached to the net (Maiello *et al*., 2022) and water samples from the catch holding tank, a basin in which fish are briefly hold before sorting (Maggini *et al*., 2024). Metaprobes are custom-made hollow, spherical probes that passively filter water while fishing (Maiello *et al*., 2022, Maiello *et al*., 2023, Russo *et al*., 2021).In pelagic fisheries, eDNA has been used with qPCR assays to estimate species abundances, including Atlantic mackerel bycatch in herring fisheries (Urban *et al*., 2022), and herring bycatch in European sprat fisheries (Urban *et al*., 2023, 2024). Furthermore, eDNA can be used as indirect proxy of the abundance and biomass of sole and plaice, two important flatfish species targeted by bottom trawl fisheries, at least in shallow waters of the southern North Sea (Maes *et al*., 2023).

Depending on factors like fishing gear, sorting methods and vessel type (see Applications in Fisheries and Pilot Studies), eDNA samples could be collected at various points along fishing operations. eDNA could be integrated into self-sampling programs, where fishers can directly collect water samples onboard. However, further testing of sampling methods and assay development is needed before widespread implementation.

eDNA-based approaches offer significant advantages to monitor fisheries compared to labour-intensive and often costly traditional methods. The advantages are related to the passive and user-friendly collection of samples, which causes little to no disruption in fishing operations and allows integration in self-sampling programs. Furthermore, eDNA analysis provides high-resolution taxonomic identification often at species-level, including species that are often reported on higher taxonomic level due to the challenging visual identification (e.g., elasmobranchs). Consequently, eDNA data is highly valuable for conservation and assessment of fishing impacts on endangered, threatened and protected species (ETPS).

2.2.1 Challenges in eDNA Data Collection

Despite its strengths, the application of eDNA faces several challenges including presence of false/positives (Gold *et al*., 2023, Maiello *et al*., 2023, Maggini *et al*., 2024), uncertainties with quantification (ref), and knowledge gaps related to the so-called “ecology of eDNA”, that is, degradation and, spatial and temporal dynamics of eDNA in the water column.

Detection issues: False negatives (i.e., failure to detect a species despite its presence) is a type of error known to emerge from the field and laboratory process level (Burian *et al*., 2021). In the field, inappropriate sampling, environmental heterogeneity, physical and hydrological factors, and DNA persistence can lead to false negatives. In the laboratory, inadequate sample conservation and/or DNA extraction, inhibition and species-specific PCR bias might result in the presence of false negatives. False positives (i.e., detection of a species despite its absence) can be the result from exogenous or cross sample contaminations occurring during sampling, laboratory procedures or sequencing (add ref) and from poor reference database quality or coverage (Ficetola *et al*., 2014, Ficetola *et al*., 2016).

Lack of biological metadata: eDNA analyses cannot provide relevant individual level biological information on phenotypic traits such as fish length and weight, and sex, age and maturity, which are essential for assessing bycatch below size limits and stock assessment models. Recent research, however, has shown promising results for the use of environmental RNA for determining developmental stages (Parsley & Goldberg, 2024) , environmental DNA methylation in tracing the spawning activity of fish (Hirayama & Minamoto, 2024). Furthermore, some preliminary research is being conducted to assess the use of eDNA to determine sex ratios based on sex-specific markers (Sigsgaard *et al*., 2019).

Dynamics: Several knowledge gaps remain on the effect of environmental and hydrological variables on the persistence and degradation of eDNA in the water column, which in turn affect species occurrence data (Joseph *et al*., 2022). Furthermore, temporal and spatial dynamics of eDNA require more research.

Quantification: Detecting rare species and determining minimum detectable biomass are further challenges to address before full implementation. Moreover, transitioning broad species analysis using metabarcoding methods from species detection to quantification, estimating the relative contribution of each species in the catch, also require further studies and species-specific calibration parameters through novel approaches like mock community experiments (Gold *et al*., 2023, Guri *et al*., 2024, Shelton *et al*., 2023).

Key challenges, therefore, include reducing false positives and negatives, improving species-level taxonomic assignments and moving from species detection to quantification. Integrating eDNA with electronic monitoring (EM) could help address these issues, as the methods complement each other, allowing for more precise species-level catch estimates. Coupling eDNA and EM could also facilitate the development of calibration parameters, enabling accurate full-catch enumeration and species contribution estimates from eDNA metabarcoding.

Applying it across different fisheries (e.g., pelagic, demersal), regions and vessel types would provide a comprehensive dataset to explore diverse catch types and fishing patterns. Such extensive sampling could support the development of reliable methods, applicable in different scenarios, to provide methods which can inform management and optimise future implementation strategies. This will yield data to support bycatch reduction strategies, conservation of vulnerable species and compliance with relevant regulations.

3. Applications in Fisheries and Pilot Studies

To validate the framework and minimum requirements outlined in this blue paper, five pilot studies will be conducted across diverse fisheries within the OptiFish project (Figure 1). These pilot studies serve as real-world testing grounds, providing insights into the practicality, adaptability, and effectiveness of advanced monitoring technologies. Each study has been carefully selected to represent distinct fisheries contexts, encompassing variations in geographical location, fishing methods, and catch handling. By examining the performance of these technologies under different operational conditions, the pilot studies aim to highlight their potential for widespread adoption and contribute to shaping best practices for sustainable fisheries management. The findings from these pilots will also inform further refinements of the technologies, ensuring their alignment with industry needs and policy requirements.

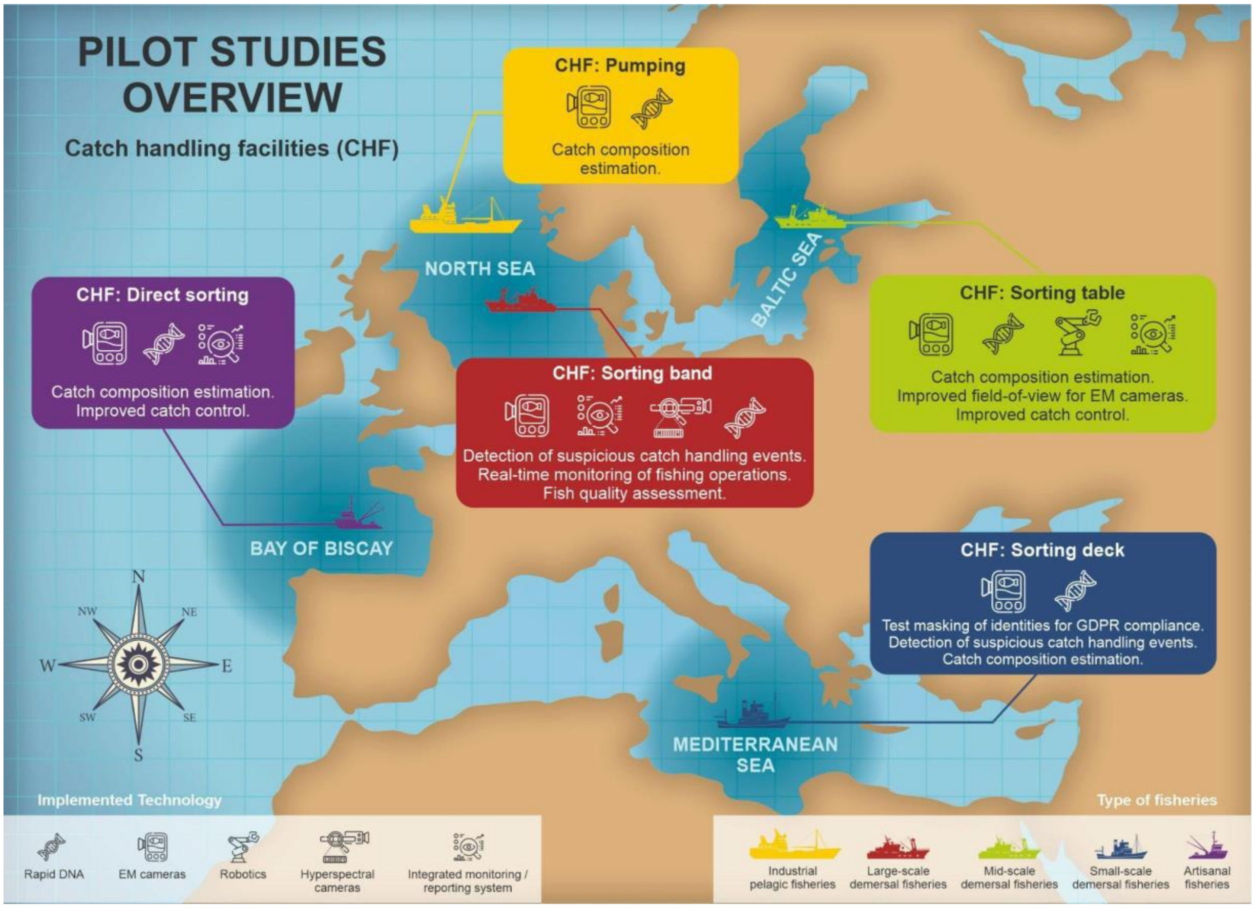

Figure 1. The division of the pilot studies based on the catch handling facilities on board, by region and fishery.

3.1 Pelagic pumping

This pilot addresses pelagic fisheries targeting small pelagic species such as herring, mackerel, horse mackerel, and blue whiting and where catches are pumped on board. Data collection involves using EM cameras and eDNA analysis onboard pelagic trawlers. Due to the unique catch handling processes in these vessels, where species are pumped onboard and stored in water tanks, standard visual monitoring may not capture all individuals. The activity aims to develop and test methods to scale EM data to total catch volumes and compare the accuracy and cost-efficiency of these methods with eDNA-based approaches. The results will contribute to benchmarking the technologies and addressing challenges in estimating catch compositions.

Pelagic fishing vessels equipped with pumping systems are diverse in layouts. To showcase this diversity, Figure 2 contains a few sample images from EM cameras installed on various pelagic fishing vessels. These are the raw image/video data formats used in the project to document catches. Given the diversity, the data acquisition for each of the pilot studies is adapted to each specific vessel.

Figure 2. An example of an image acquisition scene from an electronic monitoring camera overlooking the dewatering system onboard a pelagic vessel.

Data collection

The data collection will take place on Danish pelagic vessels, which range from 48 to 92 meters in length. These vessels pump their catches from trawls into Refrigerated Seawater (RSW) tanks, with dewatering systems separating water from the fish. EM cameras positioned at these systems capture footage of the fish, enabling catch composition estimation. Due to large catch volumes (100-1000s of tons), sorting is performed onshore, hence this task will focus on comparing EM video data to species composition identified through eDNA analysis of water samples from RSW/storage tanks.

The placement of the dewatering system varies, being either below deck (indoors) or above deck (exposed). In both cases, challenges include water and salt accumulation on camera lenses and inconsistent lighting, depending on the system's location (more controlled indoors). Dewatering boxes average 4-6 m², and EM cameras can typically detect the entire area.

eDNA samples will be collected from storage tanks immediately after fishing trips, before unloading begins. These tanks usually hold up to 70% fish and 30% refrigerated seawater (percentages can vary), with cooling maintained at -1.7°C through recirculation. Tank configurations differ across vessels, with some sharing a connected cooling system and others operating independently. This variability will be accounted for during eDNA sampling and analysis.

To date, EM cameras are installed on existing vessel infrastructure, typically 3-5 meters from the dewatering system. Camera placement aims to fully monitor the dewatering area, minimizing blind spots, though some cameras are angled due to space limitations. Video recordings during the dewatering process will be in HD quality (up to 20 FPS) to ensure species can be accurately identified using the YOLO model. Individual video frames will be processed to detect fish masks, with the frame selection scaled to estimate the full catch composition. Variations in fish flow speed may pose challenges for accurate estimates.

Regarding the eDNA sampling, three 15 mL water samples will be taken per tank using sterile syringes, with precautions to prevent contamination (Figure 3). Sampling will test whether eDNA signals are uniform across interconnected tanks or tank-specific. Vessel logbook data, including haul timing, water circulation system details, and tank temperatures, will be recorded to support accurate eDNA analysis. The full catch enumeration conducted during the pilot studies will provide an accurate list of bycatch species, enabling the evaluation of eDNA analysis efficacy by identifying false negatives and positives and establishing thresholds for species detection. The eDNA samples will undergo digital PCR to quantify key commercial bycatch species (Urban *et al*., 2022, 2023, 2024) and metabarcoding to broadly identify species composition and estimate quantitative contributions of each species. Metabarcoding results will be calibrated using experimental mock communities (samples with known DNA contribution for each species) to improve accuracy in estimating species contributions. Established primers and methods from fisheries research will guide the analysis, ensuring robust and reliable results (Miya *et al*., 2015, Stoeckle *et al*., 2024, Urban *et al*., 2024).

Figure 3. Examples of storage tanks used for holding the catch on an industrial pelagic fishing vessel, where water samples for environmental DNA (eDNA) analysis are collected to estimate catch composition. Each tank can hold tens to hundreds of tons of fish, typically containing approximately 70% fish and 30% water, with proportions varying by target species and season. To maintain the catch in optimal condition, refrigerated seawater at -1.7°C is recirculated and the tanks are often interconnected. **(B)** Surface view of a tank showing Atlantic herring (*Clupea harengus*) alongside a bycatch species, whiting (M*erlangius merlangus*). **(C)** Collection of water samples for eDNA analysis performed at landing facilities using a sterile syringe.

Analysis

Data analysis will involve an instance segmentation method (chapter 3) in order to detect species, with the YOLO algorithm as the primary choice due to its high speed and accuracy in detecting fish species under dynamic conditions. YOLO's established performance in object detection and counting tasks makes it a strong candidate for this application. Its suitability will be evaluated, and further decisions on segmentation methods will depend on its performance achieved.

Minimal Requirements

Minimal requirements for EM Camera Systems

28. **Placement**: Fixed above the dewatering systems, with limited flexibility, which may risk incomplete coverage of the dewatering area.
29. **Specifications**: High-resolution (Appendix 1) cameras with a maximum frame rate of 20 FPS and a standard upload rate of 5 FPS, along with appropriate focal lengths.
30. **Environmental Factors**: Weather conditions and illumination vary across vessels, especially for outdoor dewatering systems, making controlled conditions challenging.

Minimal requirements for eDNA analysis

31. **Sample Collection**: Maintain contamination-free protocols using sterile equipment and collect detailed vessel logbook data, including haul timing, water circulation systems, and tank temperatures.
32. **Sampling Scope**: Collect water samples from all tanks initially, until analysis determines the minimum sampling required for reliable eDNA signals.
33. **Bycatch Species Data**: An overview of expected bycatch species will aid in designing targeted digital PCR assays.

3.2 Sorting belt

This pilot addresses the development and application of technologies for catch documentation and fish-health assessment on fishing vessels equipped with sorting belts. Multispectral cameras and DNA will be employed to detect wildlife diseases and assess catch quality. EM cameras will also be integrated into the system for monitoring fishing activities and classifying fishing events. These technologies will be tested on Belgian demersal fishing vessels targeting flatfish. The obtained data from this pilot project with be integrated with VISTools (Blondeel *et al*., 2020), a software used as a decision support tool collecting a multitude of fisheries data, to enable real-time catch monitoring and decision-making – ultimately optimizing fishing operations and ensuring compliance with sustainable fishing practices.

Many fishing vessels equipped with conveyor belts have similar data acquisition scenes, where an EM camera is mounted on top of the conveyor belt and cropped to the specific region of interest. Yet, differences pertain, especially in regard to the specifications of the actual conveyor belt which often varies in dimensions and colour. Moreover, automatic image processing is challenged by variation in the catch, appearance of the fish, and occlusions caused by overlapping fish, as discussed in more detail in Section 2.1.5. Figure 4 provides a few sample images to illustrate the differences in layout onboard fishing vessels with conveyor belts, and the image acquisition scenes obtains from each of them.

Figure 4: Sample images from fishing vessels equipped with conveyor belts illustrating the differences in layout and the associated image acquisition scenes from the EM cameras placed above the conveyor belts.

Data collection

For this pilot study, the data collection will focus on North Sea . The catch will be captured using the camera system developed in the project VISIMII, using a 3D camera, which will be mounted above the sorting belt. These cameras will take high-quality images of the catch, and AI models will analyse them to identify species and estimate their size To assess the quality of the fish, hyperspectral sensors will measure parameters such as freshness, fat content, and potential issues like bleeding or parasites. Additionally, ~~tissue~~ samples for rapid DNA will be collected to evaluate fish health and verify molecular species identification. Additional sensor data will also be gathered during the sorting process, including essential elements like UTC timestamps, conveyor belt motion, and lighting conditions. These data points are crucial for validation and synchronization purposes.

The integration of the EM and sensor information will occur within the VISTools (Blondeel *et al*., 2020) platform, where species identification, composition, and quality indicators will be combined with environmental and vessel metadata. This integration will provide real-time insights into the catch and the conditions under which it was harvested.

The system will also focus on anomaly detection, identifying events that may suggest hardware or software failures, such as poor image quality, dirty camera lenses, malfunctioning systems, or non-compliant catch handling procedures. It will also detect unusual species or abnormal size distributions in the catch. In cases where the system detects that minimum quality standards are not met, notifications will be sent to the crew, enabling them to address any issues before they affect the data quality or the catch itself. This approach aims to simplify the existing reporting system, focusing on actionable anomalies that can be immediately addressed.

Scenario description

During the study, the catches will be fed onto the sorting belt, where the camera system from the VISIMII project will be positioned about one meter above it to capture images of the catch, with a focus on discards. Additional diffuse lighting will be installed to address the current lighting deficiencies under the sorting belt, ensuring optimal image quality for AI analysis. Furthermore, sensors will be integrated to monitor the motion of the sorting belt, lighting conditions, and time synchronization, ensuring the collection of accurate and consistent data throughout the study.

Technologies and Minimal Requirements

The VISIM system’s capability to process colour and depth images is essential for accurate fish identification on the sorting conveyor belt. By using the ZED X Mini stereo camera, the system captures both high-resolution colour images and depth data, which allows for more reliable detection and classification of fish species. The depth images provide additional spatial information, helping to distinguish overlapping objects and enhance tracking accuracy.

Given the high speed of the conveyor belt (at 30 FPS or higher), visual tracking algorithms are important to avoid double counting or misidentifying fish. These algorithms track each fish’s movement across frames to ensure it is only counted once, even as it moves along the belt.

Additionally, proper lighting is a key factor in ensuring high-quality images, as it helps to reduce motion blur and ensures clear visibility of fish features. Consistent, evenly distributed lighting will also mitigate the risk of shadows or reflections, which could distort image quality and affect the system's performance.

Next to the RGB stereo cameras, hyperspectral sensors will be utilized to estimate various quality parameters, such as the fish's freshness, fat content, and any signs of bleeding. Initial testing of these sensors will take place onshore, with potential onboard testing depending on the results and practicality of installation. The sensors must have high-resolution capabilities and the ability to detect a range of light wavelengths to accurately assess these parameters.

DNA collection will also be a crucial component of the study, with samples taken for species identification and disease detection. The collection process will follow strict sterile protocols to prevent contamination, ensuring the reliability of the data.

To integrate the various data sources, the different sensors used to track UTC timestamps, conveyor belt motion, and lighting conditions will be synchronized. These sensors must strictly respect the hard real-time requirements to ensure that all collected data aligns seamlessly for analysis.

Overall, the technologies involved in this pilot study are designed to work in harmony to provide accurate, synchronized data on the fish caught, their quality, and the environmental conditions during the sorting process.

Analysis

The Image Data Analysis will use AI-driven object-detection models like the YOLO family to process video footage from the cameras, identifying species and estimating catch composition. Anomaly Detection algorithms will flag issues such as blurry images, dirty lenses, or abnormal catches. When anomalies are detected, alerts will be sent to the crew for further action. The system will prioritize detecting hardware or software failures, such as malfunctioning cameras or software crashes, to maintain data quality. DNA Data Analysis will complement this image data.

3.3 Sorting table

This pilot addresses obtains automated catch documentation using EM cameras mounted onboard fishing vessels equipped with sorting tables. Given the wide variety in vessels layouts as well as the catch handling process pertaining to this type of fishing vessel where catches are often sorted directly from an outlet from a pounder (Figure 5), the field-of-view for the EM cameras is often severely compromised Consequently, a central part of this pilot, is the development of a mechanical device that can improve the image acquisition scene to increase the performance of automated catch documentation. The collected data will be integrated with logbook systems to develop enhanced reporting mechanisms beneficial to both fishers and regulatory authorities. This approach ensures accurate and transparent reporting of catch compositions.

Figure 5. Sample images illustrating the diversity in layouts for fishing vessels equipped with sorting tables, where camera angles and catch sorting areas pose significant challenges for automated catch documentation.

Data collection

For this pilot study, where catches are sorted on tables, video data will be collected for estimation of catch composition and lengths. The data collection environment will be Danish demersal trawling vessels which are typically 12-30 meters long. In these vessels, the fish sorting is done manually on sorting tables by the fishermen. The sorting table is normally recorded by placing cameras on board. However, it may be difficult to ensure a standard scene due to the diversity in the vessel designs. Another challenge is that the sorting area is typically diverse, where some vessels have open-air environments, some semi-closed and others entirely closed. This leads to various risks, such as over or under exposure of light, artificial lighting, and the presence of water and salt buildup, that may affect image quality. The size of the sorting area depends on the size of the vessel and the deck layout and is approximately 40 cm deep and 1–2 meters wide.

The camera placement on vessels will be strategically designed to capture the output of the mechanical sorting system, potentially integrating it within the system to maintain controlled lighting conditions. This system will operate independently, focusing solely on eliminating fish overlap on the sorting area to enhance the performance of deep learning models for species detection and length estimation.

The recorded footage from the mechanical sorting system’s output will be input into the segmentation model to assess its performance, while also gauging the mechanical system's impact on the automatic fish detection and length measurement processes.

The first step in data processing involves camera calibration, where a calibration board is captured in various orientations to facilitate accurate length measurements of the segmented fish. YOLO, a robust object detection model with segmentation capabilities, will be the primary algorithm tested in the experiments. If YOLO does not yield satisfactory results, an alternative algorithm from the Review of Technologies document will be chosen. For length measurement, the segmented fish masks will be skeletonized as a preprocessing step, with the skeleton length in pixels converted to real-world measurements in centimetres using the camera calibration matrix.

Analysis

The processing pipeline will mostly involve well-known state-of-the-art approaches such as camera calibration and instance segmentation using YOLO models. The tool specific for this task will be the mechanical system to reduce the amount of fish overlap on the sorting belt. As mentioned earlier, the mechanical system will not require any camera/sensor data to operate. Instead, it will serve as a preprocessing tool to improve species identification and length measurement. The video processing results (catch composition and length distribution) will then be transferred to catch logbook.

Minimal Requirements

34. **Camera Placement**: The camera will be positioned 60-80 cm from the sorting belt, inside the mechanical sorting box, to maintain consistent recording conditions.
35. **Camera Specifications**: The camera must have a minimum resolution of 720p, a frame rate of at least 30 FPS, and appropriate focal length and field of view.
36. **Weather Conditions**: The cameras will be housed in a box to protect against weather variations, ensuring a controlled environment. However, placement issues may arise due

to the diverse designs of fishing vessels, potentially leading to distorted recordings from overexposure or rain.

3.4 Sorting deck

This pilot addresses automated catch documentation onboard fishing vessels where catches are loaded onto the deck of the vessel from where it is sorted directly. The pilot is conducted onboard vessels from the demersal trawl fisheries in the Mediterranean and Black Seas. Since this type of catch sorting will include fishers in the recorded EM videos, a central task in this pilot is to develop GDPR-compliant masking algorithms to protect the privacy of fishers. The layouts of fishing vessels with deck sorting varies vastly. In addition, severe occlusion and an often-large distance from EM camera to the catch poses further complicates automated catch documentation. A few examples illustrating this diversity in layouts and catch handling processes are illustrated in Figure 6.

Figure 6. Sample images of the image acquisition scenes from an EM camera placed over a sorting deck.

Data collection

In this pilot study where catch will be sorted on deck, video data will be collected to estimate catch composition, detect suspicious actions, and develop masking algorithms for GDPR concerns. The data collection environment will involve Mediterranean demersal trawling vessels, typically 12-30 meters in length. Fish sorting on these vessels is performed manually by fishermen on the deck. While cameras can generally be placed on board to record the deck, ensuring a consistent scene might be challenging due to the variety of vessel designs. The open-air deck environment presents additional challenges, such as fluctuating light exposure and potential rain, which could affect image quality. The size of the sorting area on the deck varies with the catch amount, typically ranging from 4-6 m^2.

Camera placement on vessels will be strategically designed to capture the sorting deck area in high resolution, ensuring minimal obstruction to the fishermen’s operations while enabling accurate detection of Mediterranean commercial fish species. The cameras will be selected to meet the data collection requirements, balancing image quality and operational efficiency.

Video recordings will be made during the sorting process, ensuring sufficient resolution for the YOLO model to detect even the smallest fish species accurately. All relevant data, including video name, species name, box number, and fish count within each box, will be stored in a single Excel file for easy reference.

The initial processing will involve detecting the boxes in the videos, counting the fish in each box, and identifying species. Later stages will introduce variations in resolution, lighting, and camera angles to assess and improve the algorithm's performance across different conditions.

Suspicious event detection will begin by focusing on identifying fish placed outside the designated boxes. Over time, the detection will expand to include the entire sorting deck area, flagging any fish or objects outside this region as suspicious events.

Analysis

The analysis will involve using an object detection method, with the YOLO algorithm being the first choice for detecting fish species. If YOLO does not meet performance expectations, alternative methods will be considered. For detecting suspicious actions, key point detection methodologies will be used, while human detection models will be applied for body masking, with a focus on blurring the entire human body, regardless of identifiers like tattoos.

Minimal Requirements

37. **Camera Placement**: Cameras will be positioned at varying heights, up to a maximum of 3 meters, and may record the sorting area from an angle due to limitations in fixing spots.
38. **Camera Specifications**: Cameras must have a minimum resolution and frame rate of 30 FPS, with an appropriate focal length.
39. **Weather Conditions**: Environmental factors such as overexposure, rain, or lighting variations that could impact image quality need to be considered.

For data collection, high-resolution cameras will be used to ensure compatibility with modern technologies for accurate species and event detection. Recent studies show a range of camera specifications, from mobile phones with 48-megapixel cameras (Bhuyan *et al*., 2023) to 1920x1080 resolution cameras used for real-time tracking and species classification (Wang *et al*., 2023). In another study, cameras mounted on fishing vessels captured footage at 1280×720 resolution and 10 fps for species classification (Smith *et al*., 2022). Similarly, Taylor *et al*. (2020) employed cameras capturing at 848×480 resolution and 240 FPS for monitoring fishing operations (Taylor *et al*., 2020), further highlighting the variety of camera setups used in similar contexts.

Building on these findings, camera selection will aim to balance resolution, frame rate, and operational conditions. Placement will be optimized to cover the sorting deck and maximize the field of view while accounting for the vessel's structure. Since no standardized guidelines exist for camera placement in these settings, positioning will be customized to the vessel's layout to ensure optimal data collection coverage, durability, and performance in harsh marine environments.

3.5 Direct sorting

This pilot addresses automated catch documentation onboard fishing vessels where catches are sorted directly from the retrieved fishing gear. This includes both small artisanal fishing vessels and larger fishing vessels. For artisanal fishing vessels a trust-based self-reporting system for catch documentation is developed, which offers an alternative to EM systems for economically and technically constrained vessels. The feasibility of EM systems for onboard use in such fisheries will also be assessed, particularly for documenting ETP species and discards. In addition, automated catch documentation on larger vessels using EM cameras will be developed. These types of fishing vessels are characterized with significant differences in layouts, and the catch handling procedures vary according to the different fishing gears used. Examples illustrating the diversity in both types of fishing vessels are available in Figure 7.

Figure 7. Sample images from small-scale artisanal vessels where catch sorting takes place directly from the fishing gear upon or during gear retrieval (left). Sample images of the image acquisition scenes from EM cameras placed in the catch sorting areas from larger vessels where the catch is sorted directly upon or during gear retrieval (right).

Data collection

Direct sorting applies to vessels that remove catches directly from fishing gear as they are brought onboard, such as gillnets, pots, and long-lines, typically found in artisanal fishing vessels. These vessels, often under 12 meters in length, face spatial limitations for adding equipment, and their small crew sizes require simple, non-redundant data reporting systems. Many small vessels have become outdated and ceased operations after their owners retire. Therefore, the goal is to enhance their self-reporting capacity using easy-to-use digital systems that are simple yet effective in coordinating with authorities and scientific bodies.

The output of such an information system aims to provide new insights into a fishery sector that currently lacks proper documentation of catches and other scientifically relevant data. The project seeks to implement innovative solutions, such as self-reporting systems and eDNA, to improve the accuracy and ease of data collection. The need for systems that require less manual input while ensuring compliance with reporting requirements has been recognized. Authorities will benefit from these systems by receiving more complete and accurate data, reducing errors, improving monitoring, and enhancing cooperation between fishers and scientists. Various innovative technologies will be employed to improve fisheries management and support decision-making:

40. **environmental DNA** will be collected from alternative sources, such as nets (metaprobe) or blood water samples, to determine species composition and enhance fisheries management. eDNABlood water will also be used to detect and quantify DNA traces of Anisakis parasites. To achieve this, water will be filtered and analysed via qPCR (quantitative PCR).
41. **Self-reporting Systems**: Both existing and new self-reporting systems will be seamlessly integrated to collect necessary data for authorities and scientists, ensuring no redundancies, in accordance with the FLUX standard.
42. **Remote Sensing**: Deep learning algorithms will analyse satellite data to map vessel activities in areas of interest for industry and authorities, particularly for protecting resources and enforcing activity rights. The system will utilize freely available data from the European Copernicus platform (SAR and/or optical data), in combination with other data sources (such as AIS), to detect anomalies in human activities.

Analysis

43. **environmental DNA:** blood water from boxes will be sampled and filtered and analysed through metabarcoding (community analyses) for inferring the species present int he boxes (12S based primers such as teleo or Mifish) and through digital PCR (species-specific assay) to detect anisakis and key commercial and bycatch species.
44. **Remote Sensing Analysis**: Satellite data will be processed using ESA's Sentinel Application Platform (SNAP) software to reduce temporal noise. The iDPolRAD algorithm will be applied to detect potential human activities, with deep learning algorithms used to classify these activities and reduce noise from coastal zones.

4. Risk Analysis

Commercial fishing vessels, given their high level of heterogeneity in terms of size, design, and layout, present a unique set of challenges when implementing EM and eDNA sampling. This diversity, influenced by factors such as the species targeted and the fishing gear used, requires careful consideration to ensure that the collected data is of usable quality (Green *et al*., 2024). Effective EM in these environments depends on addressing several critical areas such as system design, data transmission and ensuring high-quality data collection for both EM and eDNA sampling (Willette & Carpenter, 2023).

4.1 Data collection risks

4.1.1 Data Quality Issues

Ensuring high-quality data is important for the successful implementation of EM and eDNA sampling on fishing vessels. For EM, one of the primary risks to data quality is the obstruction of the camera's sensor by physical or environmental factors. These obstructions may include substances on the camera lens, objects within the camera's field of view, or environmental conditions such as water or saltwater splashes (van Helmond *et al*., 2020). These factors hinder the camera's ability to capture clear and accurate images, which can lead to incomplete or erroneous data. To mitigate these risks, it is essential to implement regular maintenance procedures, including cleaning protocols for lenses, and establish sensor alerts that notify the crew when obstructions or image quality issues are detected. Furthermore, camera settings should be adaptable to changing environmental conditions, such as varying light levels, to prevent overexposure or underexposure that can distort image quality.

Another significant challenge is occlusion, where large volumes of fish or other objects obstruct the camera's view, limiting its ability to capture relevant data (van Helmond, Smith & Harkes, 2021). This risk can be minimized by strategically deploying multiple cameras at different angles to ensure full coverage of critical areas, such as catch handling zones, where fish are processed and sorted. In cases where only one camera is available, careful placement is critical to ensure the most comprehensive and unobstructed view possible, maximizing the quality and usability of the collected image data (Gilman *et al*., 2019).

4.1.2 Datasets

For AI models to be effective in analysing fishing-related data, they must be trained on large, diverse datasets that accurately represent the variability encountered in real-world scenarios. This includes a variety of fish species, fishing methods, vessel types, and environmental conditions. Establishing datasets that that are open access and include high-quality video footage will be essential for training AI models to recognize patterns and anomalies in the data. These datasets should be continuously updated to reflect the evolving nature of the fishing industry, ensuring that the AI-based systems can accurately adapt to new challenges and scenarios.

4.1.3 Validation of Data from Electronic Monitoring and eDNA Analyses

To ensure the accuracy and reliability of data collected through EM and environmental DNA sampling, robust validation processes must be established. The specific validation method will vary depending on the type of fisheries and the monitoring systems in use. For EM, one common approach is the review of footage by experienced experts, such as fisheries observers, who are trained in monitoring protocols and possess expertise in assessing video footage for quality, accuracy, and compliance with established standards. This process is critical in identifying potential errors or inconsistencies in the data captured by the monitoring system.

In some cases, more detailed validation may be required, such as onboard classification and measurement performed by experienced experts. These experts, familiar with onboard monitoring procedures, can use tools such as electronic measuring boards to manually classify and measure catches. This process ensures that catches are correctly categorized and measured, serving as a reliable reference to cross-check the data provided by the EM system. By comparing the data collected by the EM system with manual classifications and measurements, this validation process offers an additional layer of assurance that the data meets the required standards for both accuracy and quality.

Control experiments based on mock communities (known species composition) should be implemented to discard any unexpected results due to sampling method not being able to detect all target species, exogenous or cross contaminations, and amplification or sequencing biases. Indeed, the mitigation potential of contamination is very important (Burian *et al*., 2021) and recommendations to detect and limit potential contamination in the lab and field are provided in Sepulveda *et al*. (2020). Replicate samples can be included to reduce the chances of false negatives, although the number of replicates depends strongly on the type of study (Ficetola *et al*., 2014). Methods to improve the reliability of eDNA data related to false and positive negatives has been thoroughly reviewed in Burian *et al*., 2021. For metabarcoding studies, reference curated databases covering the target species should be used (Claver *et al*., 2023).

4.1.4 Instant User Notification System

To minimize the impact of data quality issues, the implementation of a two-way communication system could be considered. This system would provide real-time notifications to the crew when it detects anomalies or problems with the data collection process. For example, if a camera lens is obstructed or dirty, the system would alert the crew to clean the lens. Likewise, if a camera is misaligned or if the system identifies abnormalities in the image data—such as unusual catch patterns or poor-quality images—it would immediately notify the crew to correct these issues. This proactive approach ensures that the crew is aware of potential problems as they arise, enabling them to address these issues promptly, thereby minimizing the risk of compromised data quality.

The integration of such a communication system aims to streamline the reporting process by reducing the need for manual intervention. By focusing on actionable anomalies, the technology ensures that the crew can quickly and efficiently respond to issues with minimal interaction, thus enhancing overall operational efficiency. However, while this system significantly reduces the burden of manual reporting, it requires the crew to take responsibility for addressing the issues in a timely manner to maintain optimal data quality.

4.2 Data Storage and Transmission Risks

4.2.1 Data Storage Constraints

Limited storage capacity on fishing vessels is a risk that can lead to data loss, especially during long trips. As a solution, a redundant data storage system should be deployed, combining onboard storage with a cloud-based backup system that synchronizes data once the vessel returns to port. This ensures that no critical data is lost during the course of fishing operations. Additionally, near-real-time image analysis can provide a solution by allowing the system to analyse images on board and only store the extracted data rather than the full images. This significantly reduces storage requirements. However, to ensure the integrity of the data, it's crucial to guarantee that images are correctly analysed before the full data is discarded. Alternatively, storing images until it's confirmed that the minimum quality requirements have been met could be an option to safeguard against any potential errors in the analysis.

4.2.2 Data Backup and Security

Data backup is critical for ensuring that important video footage and sensor data are preserved. Backup systems should be both local (on solid-state drives or other durable media) and remote (cloud storage) to reduce the risk of complete data loss due to hardware failures. Furthermore, maintaining the security of data is essential, especially when dealing with sensitive information from EM. Encryption protocols should be employed both for local storage and for data transmitted to shore, ensuring that unauthorized access or tampering with data is prevented.

4.2.3 Data Transmission Risks

Data transmission from vessels to shore can experience interruptions or delays, particularly in remote areas where network coverage is weak. To mitigate this, a robust communication infrastructure, should be used to ensure that data is transmitted in real time, or at least as soon as the connection allows. Furthermore, redundancy in communication systems will help maintain data flow even if one channel fails.

One of the key risks in data transmission is the potential for data to be intercepted or altered. This is particularly important when dealing with sensitive or valuable data. The implementation of end-to-end encryption for data transmissions ensures that any data sent between the vessel and shore remains secure and intact.

4.3 Data Privacy and Security Risks

4.3.1 GDPR Compliance

Given the personal data that may be captured on video footage—such as faces or tattoos—it is crucial to comply with data privacy regulations like the GDPR. In practice, this means that any identifiable personal data should be masked or blurred before being stored or transmitted. By implementing automatic facial recognition and masking technology, the system can comply with privacy laws while still maintaining the integrity of the data for research purposes.

4.3.2 Anti-Tampering Measures

Ensuring that the data collected by the system is not tampered with is vital for maintaining its integrity. Anti-tampering hardware and software should be used to detect any unauthorized changes to the data or equipment. In addition, audit logs should be created to track the operations of the monitoring system, providing a transparent record that can be reviewed if any issues arise.

5. Appendix

5.1 Appendix 1

5.2 Appendix 2. Review of available technologies

Table A2.1. Hardware Components

Producer	Product Name	Product Type	Purpose	More Info
Anchor Lab	Black Box Video	Video and data capture platform	On board monitoring	Link
	Black Box Lite	Video and data capture platform	On board monitoring at small scale vessels	Link
	Mobile Fisheries App (Mofi)	Image and data capture mobile app	Small scale fisheries self-compliance App	Link
Shell Catch	Vessel Camera	Video and data capture onboard	Help automate fishing monitoring, optimizing the quality of on-board monitoring and reducing associated costs.	Link
	Coastal Camera	Video and data capture platform	Track shoreline activity	Link
	Scale Camera	Video and data capture platform	Automatically record the weight of the fish and store the information in the cloud	Link
Archipelago	FishVue LIME	Data collection platform	Monitor and access critical fisheries-related activity in real-time	Link
	FishVue MOBILE	Video and data capture platform	On board monitoring App	Link

	FishVue VANTAGE	EM device deployable on small to medium size vessels	Provide an end-to-end EM solution with high-quality data collection, cutting-edge AI tools and customized data analysis for all gear types	Link
Teem Fish	Marine Camera	Video and data capture platform	On board monitoring	Link
	PortablEM	Video and data capture platform	Complete solution for EM in small scale and artisanal fisheries	Link
	AI HUB	Video recording hardware	A complete solution for footage review	Link
Saltwater	Saltwater Intelligent Monitoring (SWIM)	Video and data capture platform	Complete EM system with two lighter versions (SWIM-Mobile and SWIM-Nano) to improve flexible usage under different conditions	Link
Satlink	SeaTube	Video and data capture platform	Complete EM system ensuring data privacy to protect from being tampered with	Link
Thalos	OceanLive	Video and data capture platform	On board monitoring	Link
Framos	FRAMOS Depth Camera D435E	Camera	Visual data collection and depth sensing	Link
Omni-C/DPTechnics/DB Marine	Concentrator	Vessel data capture device	Centralisation and transfer of data from fishing vessels	Link
VOYIS	Underwater Laser Scanner	subsea laser scanner	Underwater 3D point cloud generation	Link
Nvidia	Jetson AGX Orin	Edge computer	High speed processing of videos and images	Link
Intel	Intel NUC 10 Performance	Edge computer	High speed processing of videos and images	Link
Neousys Technology	SEMIL-1700GC Series, IP67 waterproof GPU computer with NVIDIA® RTX A2000/ L4	Edge computer	High speed processing of videos and images	Link

Advantech	MIC-733 AI Inference System based on NVIDIA Jetson AGX Orin	Edge computer	High speed processing of videos and images (industrial)	Link
Stereolabs	Zed Stereo Camera models	Camera	Visual data collection and depth sensing	Link
Daheng Imaging	Daheng MER2-302-56U3C	Camera	Visual Data Collection	Link
GoPro	GoPro camera models	Camera	Visual Data Collection	Link
Spectral Devices Inc.	MSC2-AGRI-1-A - 512x512 4 MP camera	Multi-spectral camera	On board fish damage monitoring	Link
SPECIM	Specim FX17	Hyperspectral camera	On shore spectral imaging	Link
LuxaLight	LuxaLight LED Back Light 5700K Protected (24 Volt, 140 LEDs, 2835, IP64) - BL-5700-140-200X100	Illumination	Diffuse illumination	Link
	LuxaLight LED-strip White 5800K Protected (24 Volt, 140 LEDs, 2835, IP64) - LS24W140X2835PLX	Illumination	Diffuse illumination	Link
	LuxaLight Infrared LED-strip 850nm Protected (24 Volt, 140 LEDs, 2835, IP64)	Illumination	Infrared diffuse illumination	Link
	LuxaLight LED Engine Ver Rood 735nm Beschermd (24 Volt, 108 LEDs, 2835, IP64)	Illumination	Infrared diffuse illumination	Link
Hamamatsu Photonics K.K.	X-ray line scan camera C14300	X-Ray Camera	On board X-ray imaging	Link
Spellman	XRBD Monoblock® Integrated X-Ray Source	X-Ray Source	On board X-ray imaging	Link

Table A2.2. Software Components

Producer	Product Name	Product Type	Purpose	More Info
Anchor Lab	Black Box Analyzer	Data visualization and analysis for REM systems	Integrated GIS visualization, catch quantification, species identification, image annotation	Link
	Black Box Firmware	Software controlling the operation of the Black Box Hardware	Data capture, reporting, executing AI models, video playback, remote connectivity, diagnostic checks	Link
Archipelago	FishVue FLEET	Fishing fleet information system	View current and historical fishing vessel activity updated in real-time.	Link
	FishVue FLOAT	Electronic fishing log	Allows fisheres to enter and submit their fishing log information electronically.	Link
	FishVue INTERPRET	EM dataset visualizer	Review vessel cruise tracks, verify gear deployment times and locations, and confirm “kept and discarded” catch records.	Link
Teem Fish	Video Review Platform	Catch reporting software	Purpose-designed for fisheries management and compliance, integrates with ease into most systems.	Link
Integrated Monitoring	Monitor	Data visualization and analysis for REM systems	Monotoring camera feeds, creating fishing trips, creating activities, integrating AI-models	Link
Satlink	Satlink View Manager (SVM)	Data analysis and review tool	Facilitate processing the data from the EM system, tagging footage, measuring fish sizes, and generating reports	Link
Microsoft (config ILVO)	PowerBI	Visualisation of data	High resolution and interactive visualisation of real-time data from fishing vessels	Link
Abalobi	Abalobi App	A marketplace platform associated with the app where all catches are registered	Improving the traceability of the fish caught by small-scale fishers while maintaining the fishermen as data owners	Link

Table A2.3. Available AI Models

Name	Purpose	Link to the paper (if available)	Repository (if available)
YOLOv7	Object detection	Link	Link
YOLOv8	Classification, Detection, Instance Segmentation, Pose/Keypoints, Oriented Detection	NA	Link
YOLOv9	Object Detection, Instance Segmentation	Link	Link
YOLOv10	Object Detection	Link	Link
YOLOv11	Classification, Detection, Instance Segmentation, Pose/Keypoints, Oriented Detection	NA	Link
YOLO-Fish	Fish detection	Link	Link
YOLO-NAS	Object detection	NA	Link
Faster R-CNN	Object detection	Link	NA
RetinaNet	Object detection	Link	NA
T-Rex2	Object detection	Link	Link
Megalodon	Object detection	NA	Link
Midwater Supercategory Detector	Object detection	NA	Link
AI for the Ocean Fish and Squid Detector	Object detection	NA	Link
MBARI Midwater Object Detector	Object detection	NA	Link
MBARI Monterey Bay Benthic Supercategory	Object detection	NA	Link
Segment Anything Model (SAM)	Instance Segmentation	Link	Link
MobileSAM	Instance Segmentation	Link	Link
Segment Anything Model v2 (SAM2)	Instance Segmentation	NA	Link
Mask R-CNN	Instance Segmentation	Link	Link
Detectron2	Classification, Detection, Instance Segmentation, Pose/Keypoints	NA	Link

RegNet	Image classification	Link	Link
Google Mediapipe	Key point detection	NA	Link
MMLab pose estimation	Pose estimation	NA	Link
CatchMonitor/CatchWatch (EveryFish)	Segmentation, fish classification & tracking	Link	NA
WaterMask	Underwater instance segmentation	Link	Link
YOLOv3 for discard registration	Fish detection and counting	Link	Link
Modified YOLOv5	Object detection, weight estimation	Link	NA

Table A2.4. Annotation tools

Name	**Annotation types**	**Open source**	**AI-aided proposals**	**Free/Paid**	**Cloud/Local**	**Homepage**
VGG Image Annotator (VIA)	Image, Video, Audio, and some more	Yes	No	Free	Local	Link
Supervisely	Image, Video, Lidar, Volumetric	No	Yes	Paid	Cloud	Link
Labelbox	Image, Video, Audio, Text, and more	No	Yes	Paid (Free plan available)	Cloud	Link
Label Studio	Image, Video, Audio, Text, and more	No	Yes	Paid (Free plan available)	Both	Link
LabelMe	Image	Yes	No	Free	Both	Link-1 Link-2
Labelme	Image, Video	Yes	No	Free	Local	Link
Roboflow	Image, Video	No	Yes	Paid (Free plan available)	Cloud	Link
Cvat	Image, Video	Yes	Yes	Paid (Free plan available)	Both	Link
Dive	Image, Video	Yes	No	Free	Local	Link
Black Box Analyzer	Image	No	Yes	Paid (Included within BlackBox Analyzer license)	Both	Link
Darwin7	Image, Video	No	Yes	Paid	Cloud	Link
SLEAP	Image, Video	No	No	Free	Local	Link
LabelImg	Image	Yes	Yes	Free	Local	Link
BIIGLE	Image/Video	Yes	Yes	Free	Cloud	Link
SQHUIDLE+	Image/video	No	No	Free	Cloud	Link
VARS	Image/video	Yes	No	Free	Local	Link
VIAME	image/video	Yes	Yes	Free	Both	Link

Table A2.5. eDNA approaches (Part 1 and Part 2)

Row ID	Sample type	Purpose	Name of the method	Workflow	Sampling gear
1	Blood water	Community analyses	eDNA metabarcoding	Collection of water/slush/metaprobe, filter water/slush, DNA extraction, library preparation, HTS sequencing, bioinformatic processing, output: species list with read occurrences	Collection of water/blood with bottles or with metaprobes
2	Blood water	Quantitative community analysis	eDNA metabarcoding	Collection of water/slush/metaprobe, filter water/slush, DNA extraction, library preparation, HTS sequencing, bioinformatic processing, output: species list with read occurrences	Collection of water/blood with bottles or with metaprobes
3	Blood water	Species specific detection and quantification	quantitative/digital PCR	Collection of water/slush/metaprobe, filter water/slush, DNA extraction, dPCR analyses, output: eDNA copy number of the target species	Collection of water/blood with bottles or with metaprobes
4	Tissue samples/ finclips	Species identification	DNA barcoding	collect tissue samples, DNA extraction, PCR amplification, sequencing, data analyses, output: species name	Subsampling specimens and store tissue/finclips in ethanol or freezer

Row ID	Question that can be answered?	Methodological requirements	Uncertainty	Processing time	Validation requirement

1	Which fish are present in the catch?	Availability of reference sequences of the species in the reference database; markers need to be able to distinguish species (interspecific vs intraspecific variability)	What are the thresholds to decide if a species is present? How to avoid cross contamination from previous catches?	Onshore, in dedicated DNA labs; lab workflow ~ two weeks (96 samples), sequencing two weeks, bioinformatics (2 days) and data-analyses (5 days)	List of catch composition to compare eDNA results against
2	Which species and in how high proportion in the catch?	Availability of reference sequences in the reference database; markers need to be able to distinguish species; production of DNA based mock communities where amplification efficiency of the species is estimated, allowing biomass calibration	This apporach allows for technical calibration of input and output DNA (after PCR). Still the ecology of eDNA can create species specific differences not caused by PCR. Mock communities cannot include all potential (rare) bycatch species	Onshore, in dedicated DNA labs; lab workflow ~ two weeks (96 samples), sequencing two weeks, bioinformatics (2 days) and data-analyses (5 days) This require that the DNA based mock quantitative calibration has been done in advance	High quality DNA from curated specimen in mock communities. Full catch enumeration or sub-samples of catch. Experimental validation with mixture experiments of multiple species
3	Is a target species present in the catch, and how abundant (number of specimens/biomass) is this species?	Primers and probes that only target the species of interest; sequence data of the target species and closely related species are required	What is the minimum biomass of fish that can be detected?	Onshore, in dedicated DNA labs; lab workflow roughly two weeks (for 96 samples), data analyses (1 day)	Check correlation between biomass/abundance to ensure assay is reliable
4	Is a specimen identified correctly? Especially important for species that are difficult to recognise morphologically,	DNA reference sequence need to be available, and resolution of the used marker gene needs to be sufficient (different	none	onshore, in DNA labs; lab workflow roughly (less than 24 samples) 1,5 day, sequencing + data-analyses (2 days)	none

	because of limited diagnostic features or because only parts of the specimens are available	enough from other species, similar enough within species)			

5.3 Appendix 3: EM System Providers

This appendix presents a list of available EM (Electronic Monitoring) system providers suitable for catch reporting, including tailored solutions for small-scale vessels. **While the list aims to cover a wide range of options, it may not be exhaustive.**

Anchor Lab
Specializes in developing cutting-edge EM solutions to address the ever-growing challenges of global fisheries surveillance and promote sustainable fishing practices. Anchor Lab's monitoring systems (Black Box Video & Black Box Lite) are built around the Black Box Analyzer eco-system enabling easy real-time monitoring of vessels and near real-time data analytics (including AI features) on catch & discard composition, protected species interactions and more.
Headquarter: Denmark

Website: https://www.anchorlab.net/

Integrated Monitoring
Delivers complete EM systems including videos and GPS sensors for catch and location reporting.

Headquarter: USA

Website: https://integratedmonitoring.net/ {under reconstruction as of 27/01/2025}

THALOS
Designs and delivers communication solutions and innovative analysis systems for maritime industry. Their video monitoring solution for electronic observation and fishing operations control, OceanLive, collects, records, processes and analyzes data (notably via AI) from onboard sensors (video, GPS, AI, etc.) to meet the ship's operational, commercial, and regulatory needs.
Headquarter: France

Website: https://www.thalos.fr/

Archipelago Marine Research Ltd.

Designs and delivers a variety of EM solutions suited for fishing vessels of various sizes and fisheries. Their product portfolio includes two systems with cameras: FishVue Vantage and FishVue Mobile. FishVue Vantage is an EM system for small to medium size vessels, designed to support multiple HD cameras, with 2-way cellular connectivity to enable real-time access through a specialized web-based software, whereas FishVue Mobile is an alternative solution to a complete EM system, that collects data related to fishing effort, including date, time, and location, while providing imagery on retained and discarded catch, plus catch handling using mobile phones.
Headquarter: Canada

Website: https://www.archipelago.ca/

Saltwater Inc.
Develops onboard EM systems designed to meet the needs of diverse fisheries. Their EM solutions include the standard EM system, “SWIM”, SWIM-Mobile which is designed for fisheries where the EM system needs to move between boats frequently and technician support is limited, and SWIM-Nano, which is designed for vessels in small scale, artisanal fisheries.

Headquarter: USA

Website: https://www.saltwaterinc.com/

Satlink
Designs and manufactures EM systems to help governments, regulators, and industry players better manage the fishing activity, providing solutions tailored to a wide range of vessel types and sizes – from small scale coastal fisheries to deep sea commercial fisheries. Their EM system, SeaTube, offers a full-scale solution integrating a multitude of sensors including cameras, GPS, hydraulic, rotation, light, temperature, main haul door opening, and crane scale.

Headquarter: Spain

Website: https://satlink.es/

Teem Fish Monitoring
Designs and delivers complete and scalable EM solutions, including hardware, software and storage technology needed to capture, analyze, and store fisheries data. Their offering ranges from small solar-powered wireless satellite vessel tracking units to complete image capture systems that include cameras with 360 degree pan, tilt, and zoom capabilities that take HD video and on-board systems that can remotely transmit data to shore. Besides full-scale EM systems, their product portfolio includes a portable and fully mobile EM system designed for small-scale and artisanal vessels, PortablEM.
Headquarter: Canada

Website: https://www.teem.fish/

Abalobi

Co-innovate and deploy data technologies relying on the useof smartphones for securing seafood traceability, fully documented fisheries, fair and transparent supply chains. The systems target small-scale and artisanal fishers and acts as an alternative to full-scale EM system, besides providing an ecosystem platform for fisher-to-marketplace transactions.Headquarter: South Africa

Website: https://abalobi.org/

Shellcatch

Designs and delivers EM solutions, including hardware, software and storage technology needed to capture, analyze, and store fisheries data across a variety of fisheries and vessel sizes. Their EM solution comprises of an EM camera with integrated GPS tracker and wifi-connectivity, connecting the collected data to a data platform with AI integration for event detection, through a mobile app.

Headquarter: USA

Website: https://web.shellcatch.com/

6. References

Afzali, S. F., Bourdages, H., Laporte, M., Mérot, C., Normandeau, E., Audet, C., & Bernatchez, L. (2021). Comparing environmental metabarcoding and trawling survey of demersal fish communities in the Gulf of St. Lawrence, Canada. Environmental DNA, 3, 22–42. https://doi.org/10.1002/edn3.111

Al Muksit, A., Hasan, F., Emon, M. F. H. B., Haque, M. R., Anwary, A. R., & Shatabda, S. (2022). YOLO-Fish: A robust fish detection model to detect fish in realistic underwater environment. Ecological Informatics, 72, 101847.

Allken, V., Handegard, N. O., Rosen, S., Schreyeck, T., Mahiout, T., & Malde, K. (2019). Fish species identification using a convolutional neural network trained on synthetic data. ICES Journal of Marine Science, 76(1), 342-349.

Allken, V., Rosen, S., Handegard, N. O., & Malde, K. (2021). A real-world dataset and data simulation algorithm for automated fish species identification. Geoscience Data Journal, 8(2), 199-209.

Barth, R., IJsselmuiden, J., Hemming, J., & Van Henten, E. J. (2018). Data synthesis methods for semantic segmentation in agriculture: A Capsicum annuum dataset. Computers and electronics in agriculture, 144, 284-296.

Barth, R., IJsselmuiden, J., Hemming, J., & Van Henten, E. J. (2019). Synthetic bootstrapping of convolutional neural networks for semantic plant part segmentation. Computers and Electronics in Agriculture, 161, 291-304.

Barth, R., Hemming, J., & Van Henten, E. J. (2020). Optimising realism of synthetic images using cycle generative adversarial networks for improved part segmentation. Computers and Electronics in Agriculture, 173, 105378.

Bhuyan, B., Das, M. K., & Nath, H. K. (2023). Development of a fish classification system using machine learning and freshwater fish images captured in natural conditions. *Journal of Marine Science and Technology, 30*(2), 129–141.

Blondeel, L., Polet, H., Vanderperren, E., Al Farisi, B., Allegaert, W., & Sys, K. (2020). VISTools II: Automatisering van gegevensverzameling,-verwerking en–rapportering aan boord van vissersvaartuigen.

Burian, A., Mauvisseau, Q., Bulling, M., Domisch, S., Qian, S., & Sweet, M. (2021) Improving the reliability of eDNA data interpretation. Molecular Ecology Resources, 21(5), 1422-1433.

Claver, C., Canals, O., de Amézaga, L. G., Mendibil, I., Rodriguez-Ezpeleta, N. (2023) An automated workflow to assess completeness and curate GenBank for environmental DNA metabarcoding: The marine fish assemblage as case study. Environmental DNA, 5(4), 634-647.

Cornelis, I., De Backer, A., Maes, S., Vanhollebeke, J., Brys, R., Ruttink, T., Hostens, K., & Derycke, S. (2024) Environmental DNA for monitoring the impact of offshore wind farms on fish and invertebrate community structures. Environmental DNA, 6(4), e575.

Deiner, K., Yamanaka, H., & Bernatchez, L. (2021). The future of biodiversity monitoring and conservation utilizing environmental DNA. Environmental DNA, 3, 3–7. https://doi.org/10.1002/edn3.178

Dukan, N., Cornelis, I., Maes, S., Hostens, K., De Backer, A., & Derycke, S. (2024) Vertical and horizontal environmental DNA (eDNA) patterns of fish in a shallow and well-mixed North Sea area. Scientific Reports 14, 16748.

EFCA. (2019). Technical guidelines and specifications for the implementation of Remote Electronic Monitoring (REM) in EU fisheries. European Fisheries Control Agency.

Ficetola, G. F., Pansu, J., Bonin, A., Coissac, E., Giguet-Covex, C., De Barba, M., Gielly, L., Lopes, C. M., Boyer, F., Pompanon, F., Rayé, G., & Taberlet, P. (2014) Replication levels, false presences and the estimation of the presence/absence from eDNA metabarcoding data. Molecular Ecology Resources, 15(3), 543-556.

Ficetola, G. F., Taberlet, P., & Coissac, E. (2016) How to limit false positives in environmental DNA and metabarcoding? Molecular Ecology Resources, 16(3), 604-607.

Gal, Y. Uncertainty in Deep Learning. PhD thesis, University of Cambridge, 9 2016.

Green, M. E., Hardesty, B. D., Deagle, B. E., & Wilcox, C. (2024). Environmental DNA as a tool to reconstruct catch composition for longline fisheries vessels. *Scientific Reports, 14*(1), 10188.

Gilman, E., Legorburu, G., Fedoruk, A., Heberer, C., Zimring, M., & Barkai, A. (2019). Increasing the functionalities and accuracy of fisheries electronic monitoring systems. Aquatic Conservation: Marine and Freshwater Ecosystems, 29(6), 901-926.

Guri, G., Shelton, A. O., Kelly, R. P., Yoccoz, N., Johansen, T., Praebel, K., Hanebrekke, T., Ray, J. L., Fall, J., & Westgaard, J. (2024) Predicting trawl catches using environmental DNA, 81 (8): 1536-1548.

Hirayama, I. T., Wu, L., & Minamoto, T. (2024) Stability of environmental DNA methylation and its utility in tracing spawning in fish. Molecular Ecology Resources, 24(8), e14011.

Hoban, M. L., Whitney, J., Collins, A. G., Meyer, C., Murphy, K. R., Reft, A. J., & Bemis, K. E. (2022) Skimming for barcodes: rapid production of mitochondrial genome and nuclear ribosomal repeat reference markers through shallow shotgun sequencing. PeerJ, 10, e13790.

Hullermeier, E & Waegeman, W. Aleatoric and epistemic uncertainty in machine learning: An introduction to concepts and methods. Machine Learning, 110(3):457–506, 2021. 1, 2

Jospeh, C., Faiq, M. E., Li, Z., & Chen, G. (2022) Persistence and degradation dynamics of eDNA afftected by environmental factors in aquatic ecosystems. Hydrobiologia, 849, 4119-4133.

Kendall, A. & Gal, Y. What uncertainties do we need in bayesian deep learning for computer vision? Advances in neural information processing systems, 30, 2017. 1, 2, 3

Kootstra, G. (2024). Advances in visual perception for agricultural robotics. In Advances in agri-food robotics (pp. 3-36). Burleigh Dodds Science Publishing.

Lamping, C., Kootstra, G., & Derks, M. (2023). Uncertainty estimation for deep neural networks to improve the assessment of plumage conditions of chickens. Smart Agricultural Technology, 5, 100308.

Maes, S. M., Desmet, S., Brys, R., Sys, K., Ruttink, T., Maes, S., Hostens, K., Vansteenbrugge, L., & Derycke, S. (2023) Detection and quantification of two commercial flatfishes (Solea solea and Pleuronectes platessa) in the North Sea using environmental DNA. Environmental DNA, 6(1), e426.

Maggini, S., Jacobsen, M. W., Urban, P., Hansen, B. K., Kielgast, J., Bekkevold, D., Jardim, E., Martinsohn, J. T., Carvalho, G. R., Nielsen, E. E., & Papadopulos, A. S. T. (2024). Nanopore environmental DNA sequencing of catch water for estimating species composition in demersal bottom trawl fisheries. Environmental DNA, 6, e555. https://doi.org/10.1002/edn3.555

Maiello, G., Talarico, L., Brodie, C., Carpentieri, P., Sbrana, A., Shum, P., Mariani, S., & Russo, T. (2023). Net gain: Low-cost, trawl-associated eDNA samplers upscale ecological assessment of marine demersal communities. Environmental DNA, 1–13. https://doi.org/10.1002/edn3.389

Maiello, G., Talarico, L., Carpentieri, P., De Angelis, F., Franceschini, S., Harper, L. R., Neave, E. F., Rickards, O., Sbrana, A., Shum, P., Veltre, V., Mariani, S., & Russo, T. (2022). Little samplers, big fleet: eDNA metabarcoding from commercial trawlers enhances ocean monitoring. Fisheries Research, 249, 106259. https://doi.org/10.1016/j.fishres.2022.106259

Man, K., & Chahl, J. (2022). A review of synthetic image data and its use in computer vision. Journal of Imaging, 8(11), 310.

Miya, M. (2022). Environmental DNA metabarcoding: A novel method for biodiversity monitoring of marine fish communities. Annual Review of Marine Science, 14, 161–185. https://doi.org/10.1146/annurev-marine-041421-082251

Parsley,M. B., &Goldberg, C. S (2023) Environmental RNA can distinguish life stages in amphibian populations. Molecular Ecology Resources, 24(4), e13857.

Saleh, A., Olsen, A., Wood, J., Philippa, B., & Azghadi, M. R. (2024). WeedCLR: Weed contrastive learning through visual representations with class-optimized loss in long-tailed datasets. Computers and Electronics in Agriculture, 227, 109526.

Sepulveda, A. J., Hutchins, P. R., Forstchen, M., Mckeefry, M. N., & Swigris, A. M. (2020) The elephant in the lab (and field): Contamination in aquatic environmental DNA studies. Frontiers in Ecology and Evolution, 8, 609973.

Shelton, A. O., Gold, Z. J., Jensen, A. J., D’Agnese, E., Allan, E. A., Van Cise, A., Gallego, R., Ramón-Laca, A., Garber-Yonts, M., Parsons, K., & Kelly, R. P. (2022) Toward quantitative metabarcoding. Ecology, 104 (2), e3906.

Sigsgaard, E. E., Jensen, M. R., Winkelmann, I. E., Møller, P. R., Hansen, M. M., & Thomsen, P. F. (2019) Population-level inferences from environmental DNA—Current status and future perspectives. Evolutionary Applications, 13(2), 245-262.

Smith, A., Jones, R., & Lee, S. (2022). Fishing event detection and species classification using computer vision and artificial intelligence for electronic monitoring. *Fisheries AI Applications, 8*(2), 123–135.

Stoeckle, M. Y., Ausubel, J. H., Hinks, G. & VanMorter, S. M. (2024). A potential tool for marine biogeography: eDNA-dominant fish species differ among coastal habitats and by season concordant with gear-based assessments. PLOS ONE 19(11): e0313170. https://doi.org/10.1371/journal.pone.0313170

Rodriguez-Martinez, S., Klaminder, J., Morlock, M. A., Dalén, L. & Huang, D. Y. T. (2023). The topological nature of tag jumping in environmental DNA metabarcoding studies. Molecular Ecology Resources, 23(3), 621-631.

Taylor, D., Miller, T., & Andrews, L. (2020). Early lessons in deploying cameras and artificial intelligence technology for fisheries catch monitoring: Where machine learning meets commercial fishing. *Sustainable Fisheries Science, 12*(1), 87–99.

Urban, P., Bekkevold, D., Degel, H., Hansen, B. K., Jacobsen, M. W., Nielsen, A., & Nielsen, E. E. (2023). Scaling from eDNA to biomass: Controlling allometric relationships improves precision in bycatch estimation. ICES Journal of Marine Science, 80, 1066–1078. https://doi.org/10.1093/icesjms/fsad027

Urban, P., Bekkevold, D., Hansen, B. K., Jacobsen, M. W., Nielsen, A., & Nielsen, E. E. (2022). Using eDNA to estimate biomass of bycatch in pelagic fisheries. Environmental DNA, 6, e377. https://doi.org/10.1002/edn3.377

Urban, P., Jacobsen, M. W., Bekkevold, D., Nielsen, A., Storr-Paulsen, M., Nijland, R., & Nielsen, E. E. (2024). eDNA based bycatch assessment in pelagic fish catches. Scientific Reports, 14, 2976. https://doi.org/10.1038/s4159 8-024- 52543- 0

Valdenegro-Toro, M., & Saromo, D. (2022). A Deeper Look into Aleatoric and Epistemic Uncertainty Disentanglement. In 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW) (pp. 1508-1516). IEEE. https://doi.org/10.1109/CVPRW56347.2022.00157

Wang, Z., Chen, X., & Liu, Y. (2023). AI-RCAS: A real-time artificial intelligence analysis system for sustainable fisheries management. *Fisheries Technology Today, 18*(4), 345–361.

Willette, D. A., & Carpenter, K. E. (2023). Low-cost trawl-associated eDNA sampling to reconstruct catch and demersal community composition. *Environmental DNA, 5*(2), 385–396. https://doi.org/10.1002/edn3.389

van Essen, R., Mencarelli, A., van Helmond, A., Nguyen, L., Batsleer, J., Poos, J.-J., and Kootstra, G. (2021). Automatic discard registration in cluttered environments using deep learning and object tracking: class imbalance, occlusion, and a comparison to human review. ICES Journal of Marine Science, 78(10):3834–3846.

van Helmond, A. T., Mortensen, L. O., Plet-Hansen, K. S., Ulrich, C., Needle, C. L., Oesterwind, D., ... & Poos, J. J. (2020). Electronic monitoring in fisheries: lessons from global experiences and future opportunities. Fish and Fisheries, 21(1), 162-189.

van Helmond, A. T. M., Smith, R. W. T., & Harkes, I. H. T. (2021). Electronic Monitoring for control on fishing vessels (No. C001/22). Wageningen Marine Research.

Wong, M. Z., Kunii, K., Baylis, M., Ong, W. H., Kroupa, P., & Koller, S. (2019). Synthetic dataset generation for object-to-model deep learning in industrial applications. PeerJ Computer Science, 5, e222.

Wu, Y., Colborne, S. F., Charron, M. R., & Heath, D. D. (2022) Development and validation of targeted environmental DNA (eDNA) metabarcoding for early detection of 69 invasive fishes and aquatic invertebrates. Environmental DNA, 5(3), 73-84.

Zhou, K., Liu, Z., Qiao, Y., Xiang, T., & Loy, C. C. (2022). Domain generalization: A survey. IEEE Transactions on Pattern Analysis and Machine Intelligence, 45(4), 4396-4415.

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