iMagine: AI-Powered Image Data Analysis in Aquatic Science

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Abstract

The iMagine platform leverages AI-driven tools to enhance the analysis of imaging data in marine and freshwater research, contributing to the study of ocean, sea, coastal, and inland water health. Connected to the European Open Science Cloud (EOSC), it enables the development, training, and deployment of AI models, collaborating with twelve aquatic science use cases to provide valuable insights. The platform refines existing solutions from data acquisition and preprocessing to provide trained models as a service for users. iMagine outlines various AI-based tools, techniques, and methodologies for aquatic science image processing, ensuring consistency and accuracy through clear annotation guidelines and verified tools. The preparation of training datasets, along with their metadata, ensures FAIRness and effective publishing in data repositories. Deep learning models, such as Convolutional Neural Networks (CNNs), are used for classification, object detection, and segmentation, with performance metrics and evaluation tools ensuring reproducibility and transparency. AI model drift and data FAIRness are also explored, alongside case studies on AI challenges in aquatic sciences. By implementing these practices, iMagine enhances data quality, promotes reproducibility, and fosters scientific progress in aquatic research while collaborating with projects like AI4EOSC and Blue-Cloud. The platform allows users to develop, train, share, and serve AI models on its marketplace. The AI models are encapsulated as Docker images and integrated with REST APIs to ensure their reproducibility. Researchers benefit from the platform's flexibility, which enables seamless execution of these Docker containers on both federated clouds of the European Grid Infrastructure (EGI) and High-Performance Computing (HPC) infrastructures.

CCS Concepts

• **Computing methodologies → Neural networks**; • **Computer systems organization → Cloud computing**.

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Artificial intelligence, Machine learning, Open science, AI research infrastructure, FAIR data, Ocean science

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1 Introduction

Europe has already developed an impressive capability for aquatic environmental observation, data-handling and sharing, modeling and forecasting, second to none in the world. This builds upon national environmental observation and monitoring networks and programs, complemented by EU initiatives such as EMODnet, Copernicus Marine, and European Research Infrastructures (RIs). However, successful implementation requires an increase in our overall knowledge, demanding more scientific research and improved access to observation data and analytical processing.

iMagine [58], an EU-funded project, contributes to the overarching mission of the EU to ensure healthy oceans, seas, coastal, and inland waters. It aims to establish a robust IT infrastructure for image analysis by creating and maintaining a scalable AI platform using the AI4OS [4] software stack. Additionally, the project seeks to improve accessibility through federation, ensuring a seamless environment for aquatic researchers. To enhance existing image analysis services, the goal is to improve research performance and provide virtual access to external researchers. The prototyping of new image analysis services focuses on the development and testing of prototypes on the iMagine AI Platform, with an emphasis on training image dataset labeling, model training, validation and deployment. The ultimate objective is to accelerate progress toward clean, healthy and productive oceans, seas, and coastal and inland waters. The project also seeks to capture best practices systematically from iMagine AI Platform providers and use case developers, ensuring that these insights are shared and promoted. Furthermore, iMagine aims to promote the AI platform through the European Open Science Cloud (EOSC) and the AI4EU initiatives. The vision for EOSC is to put in place a system in Europe to find and access data and services for research and innovation. This will facilitate researchers to store, share, process, analyze and reuse FAIR research outputs within and across disciplines and borders. A key part of the effort is the creation of a diverse portfolio of scientific image and image analysis services for aquatic researchers. This includes the development of trained models and FAIR datasets to support research and foster collaboration across the aquatic science community.

To effectively achieve the objectives of the project, twelve use cases in different areas of aquatic science are collaboratively engaging with the iMagine AI Platform providers. This partnership involves concerted efforts to leverage the capabilities of the iMagine AI Platform, foster innovation, and increase the collective impact on the advancement of image analysis tools and services for environmental monitoring and management in the field of aquatic research. The projects include the collection, storage, analysis, and processing of various types of imagery, such as drone imagery for waste monitoring, images from ZooScan instrument for taxonomic identification of seawater samples, underwater video images for ecological research, satellite imagery for oil spill detection, FlowCam instrument images for phytoplankton composition analysis, underwater acoustic recordings for marine vessels' detection, video images from beach cameras for seagrass bed monitoring, and microscope images for diatom-based bioindication in freshwater environments.

This work provides an overview of the iMagine project and its achieved best practices and recommended tools for productive and reproducible research providing FAIR data sets and AI models. The remainder of this paper is structured as follows: Sect. 2 provides information about the iMagine competence center and its role in helping domain scientists. It also presents the use cases that utilize the iMagine infrastructure. Sect. 3 describes the provided AI-platform. The recommended tools and the best practices are explained in Sect. 4. One case study of the iMagine project is described in Sect. 5 in detail. Finally, the summary and outlook are drawn in Sect. 6.

2 Competence Center

The iMagine competence center is composed of a diverse team of experts spanning multiple disciplines, including AI, IT, and domain-specific fields. This multidisciplinary team encompasses marine and freshwater application experts who are crucial in tailoring solutions to these specific domains. Additionally, the center is supported by AI framework specialists and IT experts who play a key role in overseeing the technical integration of AI solutions into various use cases. These experts are responsible for ensuring that the AI models are effectively integrated and function seamlessly within the broader technical infrastructure.

The iMagine AI platform itself is powered by the AI4OS software stack, which is developed by the AI4EOSC consortium [56]. This software stack provides the necessary tools and frameworks for implementing and scaling AI-driven solutions, ensuring that the iMagine platform can meet the diverse needs of its users. By combining expertise in AI, IT, and domain-specific knowledge, the competence center can provide comprehensive support to use cases, helping them to leverage cutting-edge AI technologies effectively.

As part of the iMagine competence center, we are actively involved in monitoring and supporting use cases through regular biweekly meetings. These meetings allow us to stay closely connected with the progress of each use case, ensuring that any challenges or needs are addressed promptly. In addition to these meetings, we offer a range of training sessions as part of our annual competence center workshops and webinars [5]. These sessions are designed to equip participants with the knowledge and skills required to fully leverage the resources and expertise available through the center.

In November 2023, we hosted an AI4EOSC platform user workshop [32], where users had the opportunity to engage with the platform and provide valuable feedback. We continuously collect feedback from use case experts, allowing us to refine our approach and learn from their experiences. This ongoing feedback loop is essential in helping us to improve and adapt our offerings.

Furthermore, we meticulously document the developments, achievements, best practices, and expert recommendations through deliverables. These documents serve as comprehensive guidelines for the standardization of processes and for enhancing the quality of datasets and AI models. By maintaining a clear and organized record of these contributions, we ensure that our work supports the continuous improvement of both the iMagine infrastructure and the broader community it serves.

The support provided by the competence center begins at the very start of the AI development cycle, starting with the labeling of raw data collected by the use cases. Our involvement continues throughout the entire AI development process, ensuring that each stage is carefully managed, from data preprocessing and model training to the final deployment of the AI model as a service. This comprehensive support allows us to address the specific needs and challenges of each use case, providing tailored assistance that maximizes the potential of AI technologies.

To facilitate the adoption and use of AI models, we offer various application delivery approaches, such as the iMagine marketplace and OSCAR [54] inference system, which serve as platforms for users to access and utilize AI solutions. These platforms provide a streamlined and user-friendly environment for discovering and implementing AI tools, making it easier for domain experts to integrate advanced AI technologies into their work.

As part of our commitment to transparency and collaboration, the labeled training datasets provided by use cases, which are crucial for the development of high-quality AI models, are published with corresponding metadata on Zenodo [65]. This ensures that the datasets are accessible to the broader community, promoting reuse and further innovation.

Furthermore, based on the lessons learned from use case experiences throughout the entire AI development cycle, we have published a comprehensive best practices document [8]. This document consolidates the insights and recommendations gathered from real-world applications, offering valuable guidance to both current and future users on how to optimize AI model development, improve data quality, and ensure successful implementation. In the following, we will introduce briefly the iMagine use cases and their objectives.

2.1 Use Cases

The iMagine project includes twelve AI/ML use cases (five mature, three prototype, and four additional use cases) from the field of aquatic sciences. Five mature use cases (UCs) concern AI-based image services and image repositories. Their AI-models are fine-tuned and available on the iMagine platform, using the iMagine framework and technical support. In practice, these services are in production, including application building and providing user documentation, while supported by an increased capacity of computing and storage resources. Three immature use cases focus on image services with high potential for uptake of AI in their analysis process. These use cases will be brought to the prototype demonstration level, making full use of the iMagine framework installations and expertise of the iMagine Competence Center and the synergy with the other use cases, both immature and mature. These use cases joined us from the beginning of the iMagine project. They are diverse in their subdomain, but all belong to aquatic sciences. By the start of the iMagine project, most of the mature uses cases were advanced in the operation of their services, while the prototype use cases started with collecting and annotating their datasets. The external or additional use cases (AUCs) joined us via the open calls of iMagine. These use cases are described shortly in the following.

UC1, Marine litter assessment. It aims to establish an operational service on the iMagine platform for the collection, storage, analysis, and processing of drone imagery used to observe waste floating on the surface of seas, rivers, and lakes and lying on beaches and coasts, and to provide standardized, classified waste datasets suitable for environmental management and indicators. The expected impact is significant, contributing to environmental management, clean-up operations, and supporting EU directives on marine strategy and the Green Deal.

UC2, Taxonomic identification of zooplankton using ZooScan. This aims to set up an operational image processing service on the iMagine platform focusing on the processing of zooplankton images acquired with the ZooScan instrument. ZooScan is a waterproof flatbed scanner that allows imaging of fresh or preserved plankton samples. It targets organisms from about 300μm to a few centimeters. It is coupled with a dedicated software that processes the images to crop and extract all imaged objects [26]. It is used to process samples taken at sea in current oceanographic cruises and historical samples from long-term collections, stored in formalin. After an initial development in a research laboratory, it is now a commercially available instrument with over 300 units worldwide and many active users. The overall objective is to create a workflow that acquires, stores and processes images of marine water samples, together with the associated metadata, and uploads the resulting regions of interest to the EcoTaxa platform for taxonomic identification. By using classical image segmentation and measurement methods, together with AI techniques (deep segmentation) on the iMagine platform, the project aims to accelerate manual handling and processing and increase efficiency.

UC3, Marine ecosystem monitoring at EMSO sites (OBESEA, Azores, SmartBay). Three EMSO sites aim to use the iMagine platform and implement AI models to automate and improve the analysis of underwater video imagery at the EMSO sites, namely EMSO-Obsea, EMSO-Azores and EMSO-SmartBay. The objective is to automate the extraction of valuable biological content from extensive datasets to facilitate scientific research and ecological understanding. At EMSO-Obsea, the focus is on training a Deep Learning service to obtain species abundance data from underwater camera images to provide insight into the impact of climate change on the local fish community [10, 22, 49, 50]. At EMSO-Azores, the project aims to develop AI models that automatically annotate and validate submarine images, improving the efficiency and accuracy of data validation [59]. In EMSO-SmartBay, AI will be used to detect and flag low-quality video footage in real-time, enabling efficient data management and analysis. EMSO-SmartBay is also looking at underwater video and imagery for marine species detection and evaluating labelling tools and Machine Learning to assist in Nephrop (prawn) burrow complex surveys.

UC4, Oil spill detection from satellite images. This aims to enhance the OKEANOS [2] oil spill monitoring service by establishing a platform for automatic processing of satellite imagery. Through the use of AI, the service improves oil spill detection accuracy and forecasting, addressing the challenges of quantifying uncertainties. The expected impact is optimized monitoring results for professional users and increased accessibility for researchers [9].

UC5, Taxonomic identification of phytoplankton using FlowCam images. It aims to establish an iMagine platform service for processing FlowCam images to determine the taxonomic composition of phytoplankton samples. FlowCam is a precision instrument that captures high-resolution digital images of subvisible particles and microorganisms in a flowing liquid [57]. The objectives include setting up an operational environment, refining the AI tools for taxonomic identification, and improving the FAIRness of the data. The result will be an understanding of phytoplankton communities, which is essential for assessing the state of marine ecosystems. It is expected that the FlowCam processing pipeline in iMagine will attract more users and image providers and contribute to efficient biomonitoring. So far, the pipeline of the module is up and running, and the AI module is available via the iMagine marketplace [55].

UC6, Underwater noise identification from acoustic recordings using spectrograms. This aims to develop a prototype for a service on the iMagine platform to analyze underwater acoustic recordings to detect and classify marine vessels. Development activities include developing a data pipeline from the sensor to the database, building a validated sound database, training models on underwater sound, connecting the database to the iMagine platform, and building the service. CNNs are used to predict the absence/presence of a vessel near the hydrophone, and to predict at which distance the vessel is situated. Using these models, a domain scientist will have the necessary tools to process acoustic underwater recordings to identify the presence, distance, and type of vessel detected. The final goal is to demonstrate that such classifiers could be used as a reliable autonomous monitoring system in maritime environments [64].

UC7, Posidonia oceanica berms and rip-currents detection from beach monitoring systems. This aims to develop a prototype for a service on the iMagine platform to process images from beach imaging systems to automate the extraction of important coastal features. It includes determining the shoreline position, monitoring Posidonia oceanica berms (Pberms) formation, and detecting rip currents. The current challenge is that processing images from existing fixed systems, namely SIRENA-sets of cameras mounted at rooftops overlooking the beach-, and CoastSnap-smartphone holders, positioned at easily accessible beach vantage points for public use, require substantial manual intervention due to varying conditions (e.g., light) and complex features (e.g., amorphous rip currents and Pberms). This limits their effectiveness in continuous monitoring. To address these challenges, the use case proposes using Deep Learning techniques for image segmentation and object detection. This approach aims to reduce human intervention, allowing for more consistent and detailed monitoring of beach dynamics, crucial for understanding beach changes and ensuring the safety of beach goers.

UC8, Identification of freshwater diatoms using microscopic images. The use case aims to develop a diatom-based bioindication service on the iMagine platform using automatic pattern recognition algorithms for individual microscope images from freshwater environments. Diatoms, essential bioindicators of freshwater ecological health, are traditionally identified through laborious microscopic examinations. The prototype will utilize AI, specifically CNNs, to automate diatom classification based on morphological features [60–62].

AUC1, Satellite-Derived Bathymetry. The objective is to fully automate the Satellite-derived bathymetry from the download of satellite images to the final production of bathymetric maps, using the latest machine learning (ML) and deep learning (DL) techniques. Additionally, the aim is to advance the generalization of a model capable of working accurately in diverse geographical and oceanographic conditions. These new techniques have already been tested with good and promising results in local areas of the Mediterranean Sea, making temporal and spatial predictions of bathymetric maps of beaches.

AUC2, improving knowledge about Cold Water Coral Reef. This aims to develop a non-destructive method for evaluating the coverage of cold-water coral reef species. This involves using segmentation models for the identification and calculation of coral coverage in underwater images obtained through oceanographic surveys, facilitating multi-temporal comparisons and enabling quantification of both live and dead coral matrices. This methodology is crucial for understanding the evolution of these ecosystems, their response to environmental factors, and for preserving their biodiversity and health within broader research and conservation frameworks [24].

AUC3, AI for image-based age reading from fish otoliths. This aims to develop an AI algorithm to estimate the age of a fish from an image of an otolith. Otoliths are calcified structures, also called ear stones, which are found in the head of a fish. Age readers estimate the fish age by counting growth rings, which are laid down annually in the otolith. This is a highly subjective and time-consuming process. Building an AI algorithm to determine the age of the otolith, based on an image, aims to improve the accuracy and precision of the age data used in internationally agreed stock assessment models as well as supporting quality control procedures applied in age reading labs internationally.

AUC4, Validating images collected with the EyeonWater app. This aims to assess the ocean's water quality using images captured by regular citizens. This helps researchers classify rivers, lakes, coastal waters, seas, and oceans by color. To assist in determining whether an image meets the criteria for inclusion in the app, the YOLOv8 model [52] for image classification is employed. If the model deems a water image unsuitable, it is excluded from the app's online database.

3 AI Platform

The iMagine platform is built on the open-source software framework AI4OS [4], developed by the AI4EOSC project [56]. The platform aims to provide AI tools designed for use cases in the aquatic science domain, supporting AI model development and the creation of AI-based services. For each step in the AI development life cycle (Figure 1), from data collection and preprocessing to model training, evaluation, and deployment, the platform provides dedicated means that ensure best practices and optimize performance. This comprehensive approach facilitates the efficient development, testing, and deployment of AI models, enabling researchers and developers to seamlessly achieve their goals.

Figure 2 depicts the general platform architecture, where use case developers interact primarily with the iMagine marketplace and the dashboard. While the marketplace is open to everyone, authentication through the EGI Check-in service [23] is required to access most of the platform's features. The EGI Check-in is a proxy service that connects federated Identity Providers, allowing users to authenticate via their institutional accounts or public ones like ORCID or GitHub. All assets on the marketplace are provided with rich metadata that includes e.g. AI tasks, libraries, licenses, GitHub repositories for the source code, and Docker Hub for easy deployments. This metadata ensures the accessibility and reproducibility of the applications. Authenticated users can try every application for inference for up to 10 minutes. Using more advanced AI4OS services, such as training, MLflow [18] tracking, storage, or adding one's own application, requires users to be members of the iMagine Virtual Organization (VO). Currently, these use cases are listed in Section 2.1, and more users can apply for membership through rolling Open Calls [34].

To begin development, registered users can either derive their application from an existing AI model available on the marketplace or develop one from scratch using predefined software templates [6, 43]. Each user is provided with a GitHub repository under the AI4OS-Hub organization to keep their source code under version control. JupyterLab and VS Code integrated development environments (IDEs) are available for code development directly on the iMagine platform. The platform supports linking with storage systems, currently, NextCloud-type but the connection with other storage systems is possible through the Rclone utility [21]. Once the storage is linked, users can utilize datasets either from the platform's storage or by querying and loading their desired datasets from Zenodo or other supported repositories using DOIs and URLs. Supported repositories include GitHub, SEANOE, Hugging Face, Mendeley Data, and others. To support this, the iMagine platform uses an open-source downloader Python tool, called Datahugger [19]. The CVAT [16] annotation tool (see Section 4.2)

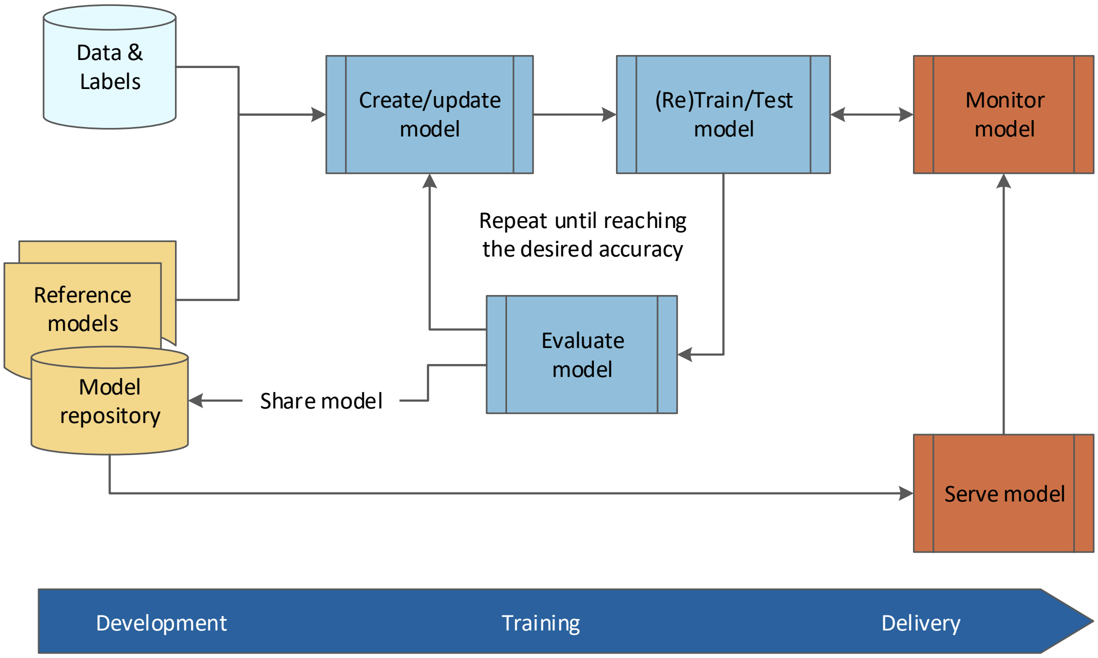

Figure 1: AI development life cycle.

can be deployed on the platform, allowing users to bring their raw data, store it in the Nextcloud storage, and create annotations for training dataset preparation. To track various AI experiments during the training phase, the MLflow tracking server is provided following the MLOps approach. Users who wish to keep their data private can leverage Federated Learning AI methods [47] and deploy the Federated Learning server [56] on the platform, while keeping both data and training processes on their own sites.

The iMagine use case developers collect and prepare labeled datasets for training their applications. Once the training dataset is complete, it can be published in the Zenodo data repository. A FAIR evaluation of the datasets' (meta)data is conducted using the FAIR EVA tool [3] (see Section 4.3).

As soon as users train their own AI model, it is coupled with the DEEPaaS API [45], the REST API for Machine Learning and Deep Learning models, and is encapsulated as a Docker image, forming a single AI module. DEEPaaS API also provides a command-line interface, deepaas-cli, allowing users to execute the identical workflows via the command line. Together with container tools like udocker [25] or singularity [41], this enables the execution of AI modules also on High-Performance Computing resources. Once completed and tested, the AI module is added to the iMagine marketplace for sharing with the aquatic science community (Figure 3). The marketplace also offers an inference service, allowing trained AI models to run on the connected backend cloud resources. The AI modules available on the marketplace can be deployed by any logged-in user (for 10 minutes) as inference web applications based on Gradio [1] using the "Try" button on the dashboard, or by use case developers as long-running services in the OSCAR inference system [54]. OSCAR is the serverless event-driven computing component of the platform, based on Kubernetes [40], CLUES [14], and Knative [39] for horizontal scaling of computing resources in and out in a serverless manner. OSCAR supports multi-tenancy so that end users of AI services can keep their data and inference private if needed. Another deployment option is through the Infrastructure Manager (IM) [12], which allows any authenticated user to deploy AI modules from the marketplace on their own cloud resources.

A user who would like to retrain an existing module on their own dataset can retrain the module locally (since all the code is open source). However, the iMagine platform enables users to retrain models on cloud resources via the Dashboard. To accomplish this, the user uploads the dataset to AI4OS-Nextcloud storage, deploys the AI module which is automatically connected to the storage, and retrains the module using the DEEPaaS API.

The platform architecture is based on a Platform-as-a-Service cloud computing model, where both hardware and software resources are managed and users can focus on the application development. The CPU and GPU computing resources are federated across various cloud providers from the EGI federated cloud and include: IFCA [31], INCD [37], TÜBITAK [36], and WALTON [63] providers. The federation of resources is achieved through the use of Consul [27], Nomad [28], and Traefik [42]. In these approaches, when a user launches an application workload from the iMagine dashboard, the application is seamlessly deployed as a Nomad job via the platform API [7] at one of the cloud providers with corresponding monitoring being in place. The platform API follows the Open API specification [48] and is based on FastAPI. It is extendable for other services and already supports the download of datasets from Zenodo, communicating with HashiCorp Vault for secrets management, creation of deployment snapshots for storing in the Harbor docker registry, and deployment in the inference system OSCAR.

Figure 3 shows the dashboard of iMagine Marketplace, where all deployed mature use case modules are highlighted in green and one external use case in blue. The orange boxes show the general purpose modules developed and integrated by the iMagine experts, such as YOLOv8, Faster R-CNN [53], and image classifier.

4 Best Practices and Tools on the Platform

We have learned lessons from the eight mature and prototype use cases during their whole AI developments and published them in October 2024 as Best practices for producers and providers of image sets and image analysis in aquatic sciences on Zenodo [8]. These best practices achieved from use case experiences and AI experts during the iMagine project consist of a wide range of topics listed as: deep learning models, annotation tools, data repositories and open-source dataset for Marine applications, preprocessing techniques, performance metrics and evaluation methods, tools for monitoring model performance, data biases and fairness in Aquatic science models and data, model delivery, AI model drift tools, and experiences of the use cases. In the following, we explore the tools reviewed in [8] that are already available on the platform as of the time of writing this article, offering users immediate access to their features and functionalities for streamlined implementation.

4.1 Deep Learning Models

Deep learning, a branch of artificial intelligence (AI), utilizes multi-layered neural networks to model and interpret complex patterns in data. It has transformed image processing by empowering machines to learn and identify features from raw images, eliminating the need for manual feature extraction. CNNs are a class of deep neural networks that are most commonly used to analyze visual images. They have proven to be extremely successful in various computer vision tasks such as classifying images into predefined categories (image classification), locating and identifying objects in an image (object detection), and segmenting images into different classes (image segmentation). For these tasks, we made general-purpose modules available on the iMagine Marketplace, namely, YOLOv8 and Faster R-CNN.

You Only Look Once (YOLO) models are a series of one-stage object detection models designed for real-time applications. YOLO is available in multiple versions (v1 to v11), each with improvements in accuracy and speed, focusing on predicting bounding boxes and class probabilities directly from full images in a single evaluation. YOLOv8 is provided by the Ultralytics [38] using the PyTorch framework. This model can be used flexibly for classification, detection, oriented object detection, and segmentation tasks. We have integrated the DEEPaaS API into the Ultralytics YOLOv8 and made it available as a general-purpose module on the marketplace of the iMagine platform. Depending on the application, users can select one of the model variants (nano (n), small (s), medium (m), large (l), and xlarge (x)) and train it. The Docker images are provided together with these models. Users have the option of either starting a deployment on the iMagine platform from these Docker images and training the models on custom data with minimal effort, or running these Docker containers on both Cloud and High-Performance Computing (HPC) infrastructures.

Faster R-CNN is a two-stage object detection model that introduces Region Proposal Network (RPN) to generate region proposals instead of using external methods like selective search, making it faster and more accurate. It integrates RPN with the Fast R-CNN architecture. The external repository, fasterrcnn pytorch training pipeline [51], provides a pipeline for training PyTorch Faster R-CNN models on custom datasets. With this pipeline, users have the flexibility to choose between official PyTorch models trained on the COCO dataset [44], use any backbone from Torchvision classification models, or even define their own custom backbones. The trained models can be used for object detection tasks on specific datasets. We have integrated the DEEPaaS API into this existing codebase, and this model is available to use on the iMagine Marketplace.

4.2 Annotation Tools for Data Labeling

The effectiveness of deep learning models depends heavily on the quality and quantity of the annotated training data. Annotation tools allow users to annotate images with semantic labels, bounding boxes, polygons, and key points to create annotated datasets tailored to specific research objectives and model requirements. Annotation tools such as BIIGLE, CVAT, Label Studio, and Roboflow were evaluated based on their features, as well as their advantages and disadvantages [8].

Computer Vision Annotation Tool (CVAT) is a popular tool for annotating digital images and videos, primarily developed to support computer vision tasks. There are two main free options for using this tool: Self-hosted and CVAT Cloud (limited). CVAT is licensed under the Apache 2.0 open-source license. It supports various annotation types, including bounding boxes, polygons, polylines, points, cuboids, and 3D annotations. This tool is designed for tasks such as object detection, image segmentation, classification, and more, and provides an intuitive, easy-to-use interface for annotators.

CVAT also offers serverless functions for deploying containerized applications on GPU or CPU in a local system. It supports automatic annotation with pre-trained models, including segmentation, detection, and tracker models such as the Segment Anything Model (SAM), YOLOv7, text detection v4, or TransT. Users can integrate their models for specific tasks. The installation process supports multiple platforms, including Docker-based deployments, which makes it easy to set up on various types of infrastructure. Based on the UC experiments conducted as part of the iMagine project, CVAT has emerged as the most frequently used tool by our users.

In the AI4EOSC project, CVAT is forked and adapted for deployment in Nomad. Key modifications include:

- Enabling custom port specification for services like Identity and Access Management, Open Policy Agent, Postgres, and Redis to ensure proper visibility and functionality.
- Adding a superuser creation command to handle repeated deployments in Nomad.
- Adjusting the Docker image to support AI4EOSC storage integration via Rclone, cloud storage management software,

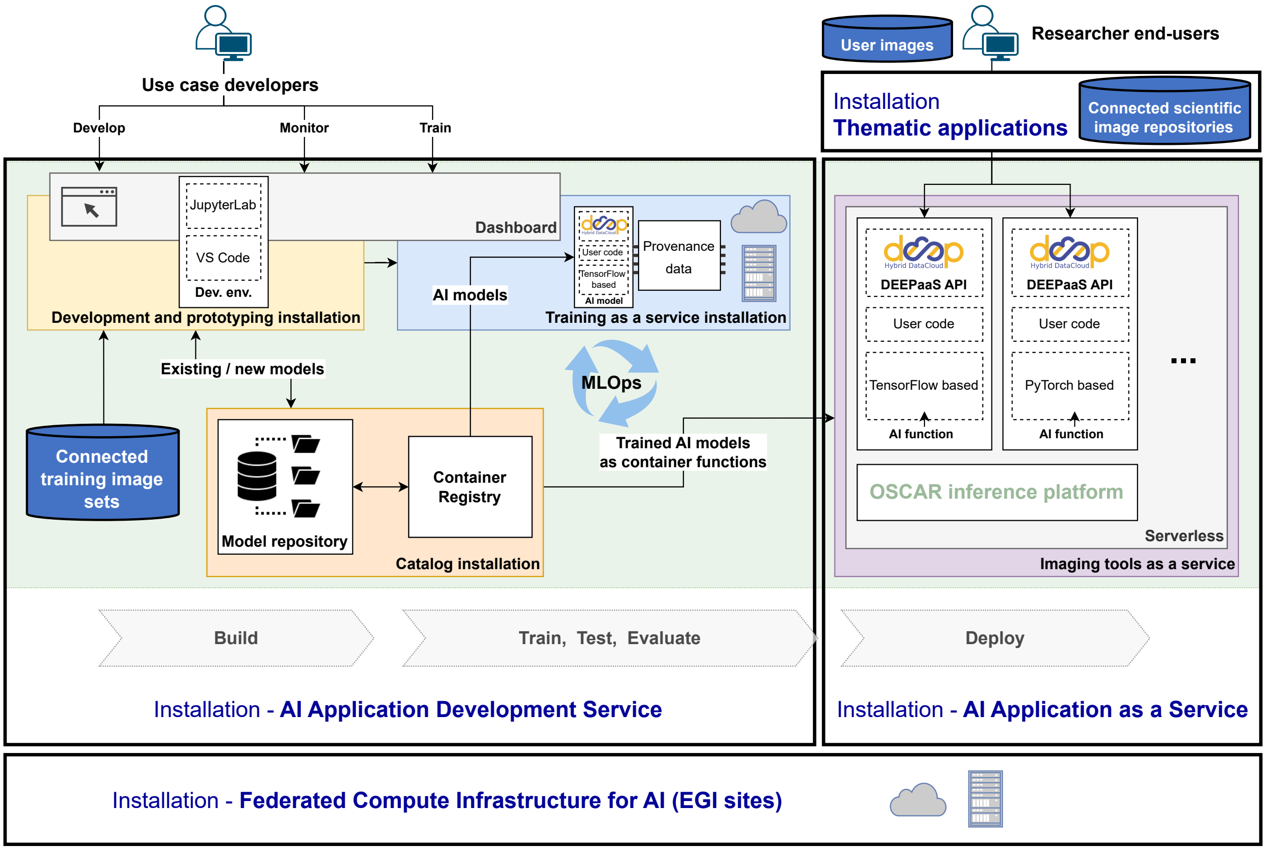

Figure 2: iMagine AI platform.

enabling data persistence and usage as a source for annotations.

The deployment of CVAT, which comprises more than 15 containers, is summarized in a Nomad job that is integrated in the platform API. This simplifies version upgrades and allows users to deploy isolated CVAT instances from the dashboard and support custom resources such as GPUs for AI-powered labeling [29].

4.3 Data Repositories for Aquatic Applications

The iMagine use cases collect, create, prepare, and use labeled datasets for training their AI models. To make these datasets accessible to external users and improve their FAIRness, iMagine created a project community on Zenodo. This is the preferred platform for data storage and sharing due to several compelling features. It offers long-term storage, assigns each publication a DOI, provides robust version control and access to specific dataset versions as needed. Zenodo also accommodates generous storage needs, offering 50 GB of free storage per publication with the option to request additional space. Finally, it provides detailed usage insights, including open download and access statistics, enabling researchers to gauge the reach and impact of their data effectively.

Twelve training datasets of our use cases have been published with corresponding metadata on Zenodo, or the metadata accessible via Zenodo and linked to other domain repositories. Zenodo serves as a general repository for various domains. As our use cases are in aquatic sciences, iMagine agreed with Zenodo via the HORIZON-ZEN project [15] for a domain-specific format of metadata. The extension and adaptation have been agreed with the Zenodo developers at CERN, European Organization for Nuclear Research, before summer 2024. The deployment of the new metadata will include configuring a dedicated Content Management System (CMS) and later also an API to facilitate a machine-to-machine exchange of the iMagine Zenodo entries. iMagine plans to launch the template and services in early 2025 and the common templates will be migrated into the domain-specific format.

To improve the management and sharing of research data, FAIR EVA, has been developed within the EOSC context. It is designed for specific data management systems, such as open data repositories, which can be tailored to individual use cases in a scalable and automated environment. The tool aims to be flexible and adaptable, supporting various environments, repository software, and disciplines, in line with the flexibility of the FAIR Principles. FAIR EVA tool in the context of iMagine has been used to improve FAIRness of published training datasets.

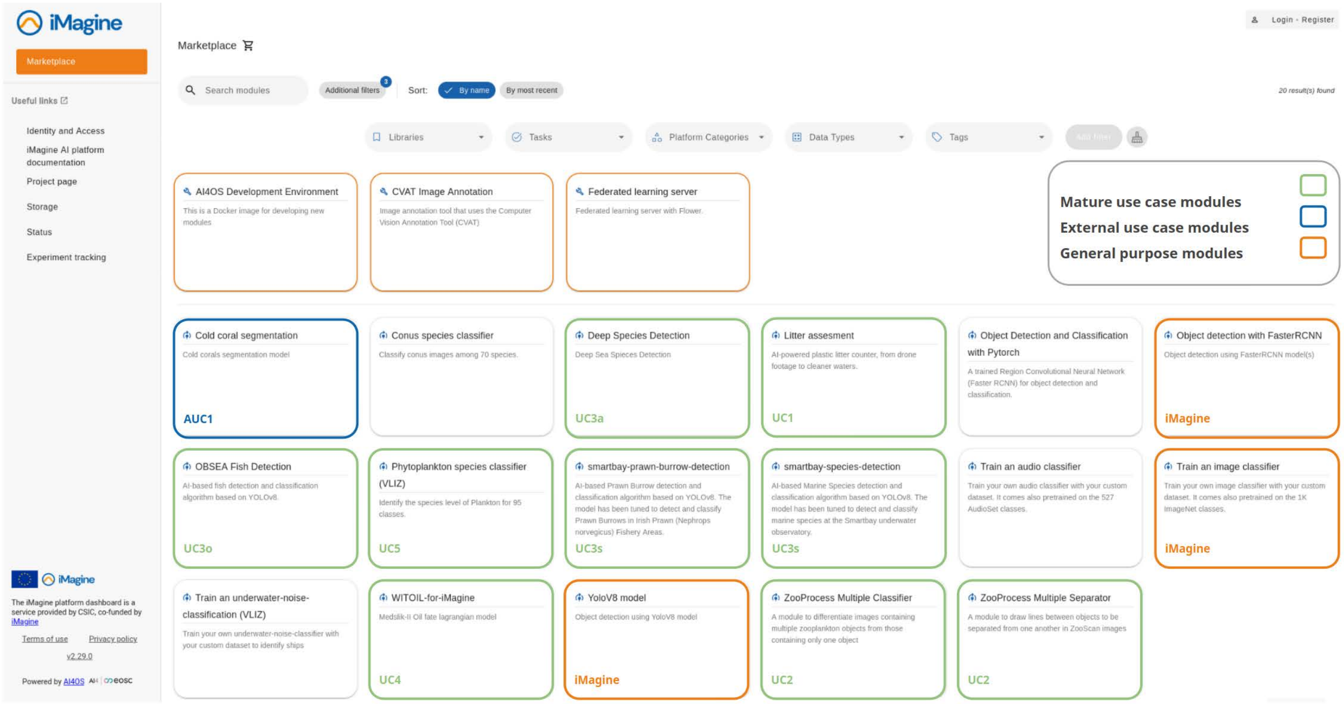

Figure 3: Dashboard of iMagine Marketplace.

Table 1: Status of mature use cases in iMagine.

Use case	Labeling	Published training dataset	Models	Marketplace delivery	OSCAR delivery
UC1	in-house tool using litter categories	✓	MobileNetV2 DenseNet121	✓	✓
UC2	labeling with EcoTaxa segmentation with current ZooProcess (both in-house tools)	✓	MobileNet Mask2Former	✓	✓
UC3-Azores	annotated by citizens (Deep Sea Spy)	✓	YOLOv8	✓	not planned
UC3-OBSEA	labelImg, roboflow Label Studio, BIIGLE	✓	YOLOv8 Faster R-CNN	✓	Work-in-Progress
UC3-SmartBay	CVAT	✓	YOLOv8 DOVER VQA	✓	not planned
UC4	proprietary method developed by ORBITAL EOS	✓	Bayesian optimization	✓	Work-in-Progress
UC5	in-house tool	✓	CNN based on Xception	✓	✓

4.4 Monitoring Model Performance

MLflow [18] simplifies machine learning development by providing integrated solutions for experiment tracking, reproducible run packaging, and seamless model sharing and deployment. It offers lightweight APIs compatible with many machine learning frameworks or libraries, such as TensorFlow, PyTorch, and XGBoost, and supports diverse environments, including Jupyter notebooks, standalone applications, and cloud platforms. MLflow offers several key features as listed in the following.

- **Model Registry:** A centralized hub for managing and versioning models.
- **Experiment Tracking:** Logs parameters, metrics, artifacts (e.g., model files), and metadata from machine learning experiments.
- **MLflow Projects:** Packages ML code in a reusable and reproducible format for collaboration or transfer to production.
- **MLflow Models:** Supports managing and deploying models from various libraries to diverse serving and inference platforms.
- **Self-Hosting Options:** Can be deployed as a self-hosted solution.

Within the iMagine project, an MLflow tracking server has been deployed, primarily for experiment tracking. An additional layer has been integrated to allow users to self-register through the project's common AAI (*EGI Check-In*) and to manage permissions for sharing experiments and models with other platform users. Automatic database backups and manual restoration capabilities have been implemented to ensure reliability. The related code, packaged as a dockerized solution, is available for deployment.

4.5 Model Delivery

The accessibility and reusability of trained AI models are important for researchers to foster collaboration and accelerate innovation. Once the AI model is trained and validated, it can be shared on the iMagine marketplace and deployed in the production of aquatic image service. The trained and validated models are integrated with API (recommended is DEEPaaS API, REST API for AI/ML/DL) and packed as Docker images. This enables external users to download the AI modules as Docker images and run them on their own or third-party external compute resources.

In addition, the marketplace offers "Marketplace inference service delivery" to run trained AI models for inference on the connected back-end cloud resources. Deploy a model in the project's OSCAR serverless inference platforms: the iMagine OSCAR clusters support multitenancy and offer accounting thanks to the Prometheus and GoAccess services. They can collect metrics like resources consumed by inference executions, the number of deployed services over a period of time or the geolocation of the users interacting with the services.

4.6 AI Model Drift Tools

In aquatic imaging services, used for monitoring marine life or underwater environments, challenges such as lighting, water clarity, camera dirt, and species behavior variability can impact AI model performance. These variations often lead to data drift, where input data distributions shift away from the model's training data, causing reduced accuracy and reliability. Drift detection tools are crucial for identifying and managing these changes, enabling continuous monitoring and early detection of data or model performance shifts to maintain accuracy and effectiveness in dynamic settings.

Frouros [17], developed as part of the AI4EOSC project, is a Python-based drift detection tool designed for machine learning systems. It supports both concept and data drift detection using 32 detectors, ranging from classical to state-of-the-art methods, surpassing other libraries in variety. Frouros offers features like datasets for testing, categorized detectors, custom callbacks, and evaluation metrics, making it a versatile and user-friendly solution for ensuring AI model reliability in complex and evolving environments.

5 Case Study

In this section, we describe UC5, Taxonomic identification of phytoplankton using FlowCam images, that is one of the mature use cases in the iMagine project. Phytoplankton has a key function in the aquatic food web and produces energy for other marine life. The use case aims to establish an operational service on the iMagine platform for ingestion, storage, analysis and processing of FlowCam images (300-400,000 particle images per year) for determining taxonomic composition of phytoplankton samples [55]. CNN models based on Xception architecture [13] have been trained on manually validated FlowCam images of phytoplankton cells to speed up identification of particle images. Adaptation of model Parameters and determining classes to stain on is done through Python scripts. The existing workflow is improved by leveraging the iMagine AI platform.

This use case addressed several challenges through using the iMagine AI platform. First, the existing in-house data ingestion pipeline from sensor to database is optimized to enhance efficiency. Additionally, metadata and data output formats are improved to ensure compliance with community-based standards and vocabularies. The service has been refined to incorporate contextual input, thereby increasing classification accuracy. The training dataset is extended by identifying additional particles that have already been grouped under a general "rest" class. Furthermore, data and processing components are prepared for connection, synchronization, and migration, enabling seamless access from the iMagine platform.

The current model was trained on the training dataset available on Zenodo [20], which is annotated with an in-house tool. The FlowCam phytoplankton identification module was developed on the iMagine platform, allowing users to customize the train/validation/test split and apply data augmentation using the Python Albumentations package [11]. The model employs a categorical Cross-Entropy loss function for classification. This module is largely based on the general-purpose image classification module provided by the platform module [46]. Computing resources from iMagine were utilized to train the model. It is one of the first modules made available for deployment of inference in OSCAR, and external users were introduced to the module, allowing them to request access and use the service.

Addressing class imbalance in the dataset, thresholds were established during training set sampling to ensure a minimum of 100 images per class and a maximum of 10,000. Augmentation techniques are used to upsample rare classes and are available through the FlowCam module on the iMagine platform. The module also includes functionality to handle variations in image resolution and color formats across different FlowCam devices. Model performance is evaluated using Jupyter notebooks to compute metrics like Precision, Recall, and F1 score.

A fully functional FlowCam phytoplankton identification service is accessible via the iMagine platform. Users can deploy a pre-trained FlowCam model capable of recognizing up to 95 classes for analyzing new data. Additionally, the model can be retrained on a customized dataset when collaborating on a new use case. The service includes several Jupyter notebooks that enhance functionality. These allow users to assess model performance and identify high-certainty predictions. Some Jupyter notebooks focus on data augmentation to address class imbalances, which are common in plankton imaging datasets. Comprehensive user documentation has been added to a GitHub repository [30], providing guidance on optimizing the use of the service.

6 Summary and Outlook

In this paper, we introduced the iMagine project and its objectives to empower Aquatic scientists with a productive IT/AI infrastructure and tools toward healthy oceans.

Table 1 summarizes the current status of the mature use cases in iMagine: all deployed their models on the marketplace and published their training datasets. UC1 and UC5 use also OSCAR platform to deploy their inference services and have new users for their models. The other use cases are in progress to integrate OSCAR in their services. As an end user, one can discover and use the AI services of the iMagine mature use cases from the iMagine website [33]. Some use cases are already available and offer their services, so that one can request access via filling out this form [35] and will be informed about how to use the service.

iMagine is an ongoing project that in the first stage continues until the end of August 2025. During this period, the Competence Center continues the monitoring and supporting of its use cases. In the future, it will extend the best practices for AI-based image analytics services and publish as open-access. Furthermore, the prototype use cases will be validated and made ready for the way to deploy.

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