# CHAPTER 1. INTRODUCTION

## 1.1 Project Background

Microorganisms that passively drift in water currents are called plankton and constitute a key part of a fully formed aquatic ecosystem. Measuring from a few micrometers to several millimeters, plankton contain heterotrophic organisms (zooplankton) and photosynthetic (phytoplankton) microorganisms. Within the planktonic community, the photosynthetic part, including flagellates, dinoflagellates, and diatoms, produces around half of the oxygen we breathe and fixes almost 40% of the global carbon each year (Bachimanchi et al., 2023). Therefore, phytoplankton fuel a large portion of the energy available in the ecosystem. On the other hand, zooplankton, as the primary consumers of phytoplankton, facilitate energy transfer to the large consumers of the ecosystem, including fish, marine mammals, and other predators. The considerable variety in the sizes of towering organisms in the pelagic zone, including picophytoplankton, which are organisms of 0.2-2µm in length, and microplankton, which are organisms of 20-200µm in length, has a direct impact on the proficiency of energy movement throughout the marine biological community, and food web in particular, which has been commented on by the study of Yue et al. (2023).

Dominating the world's countries in the number of islands within its borders, Indonesia holds an unparalleled position in global marine biodiversity. Its regions encompass 76% of the world's coral and 37% of coral reef fish species, spanning the Makassar Strait, Banda Sea, and Java Sea, which are part of the Coral Triangle Region (Global Fund for Reef Corals (GFCR), 2023).This study segmented the identification coverage area into Western and Eastern Indonesia, which reflect the oceanographic influence of the Indonesian Throughflow (ITF) or locally, Arlindo (Arus Lintas Indonesia), where the seasonal nutrient flux patterns have a directly shape on the composition and distribution of regional phytoplankton (Horii et al., 2023; Tapia et al., 2022; Taufiqurrahman et al., 2020). Indonesia's plankton communities, estimated at 150–400 phytoplankton species sustain the livelihoods of more than 6 million Indonesians who depend on coastal fisheries and marine resources (World Bank, 2021).

Additionally, Indonesia faces the compounding pressures of climate change, coastal development, and the growing fishing industry. Thus, the identification and evaluation of Indonesian plankton communities become instrumental to fulfilling Sustainable Development Goal 14, particularly Target 14.a (Life Below Water), and Sustainable Development Goal 4, particularly Target 4.7 (Quality Education). Both goals require enhancing scientific understanding and reducing barriers to participation in marine science at all levels. Particularly in Indonesia, identifying invasive plankton species is necessary at the meeting point of the Pacific and Indian Oceans, where international shipping routes with ballast-water exchange practices threaten the local marine community structure.

## 1.2 Problem Statement

In Indonesia, to subclassify an organism, a taxonomist must use a light microscope for manual identification. According to Pierella Karlusich et al. (2022), the process is very costly and time-consuming, and it requires highly specialized training. As Pastore et al. (2020) describe, datasets used for plankton research are increasingly digital, and manual annotation is no longer feasible. In the tropical regions of Indonesia, highly turbid waters and a diverse plankton community make manual identification time-consuming, underscoring the need for an automated, web-based identification system for a locally built Indonesian dataset.

At present, no existing online platforms integrate data augmentation and transfer learning with Indonesian plankton datasets. Although Pitois et al. (2025) acknowledge progress in transfer learning, current systems, such as RAPID, are designed for specific temperate geoclimatic zones and are inappropriate for the organismal and sedimentological complexity of Indonesian tropical waters. In such waters, Maracani et al. (2023) state that the classification is even more complex and requires bespoke solutions. Addressing local needs, developing a web-based deep learning system for data augmentation that simulates tropical conditions is the optimal solution to enable quick and precise identification of plankton species.

Limited surveys affect ecosystems and the management of the archipelago's 17,500+ islands, hindering achievement of SDG 14 Target 14.a, which calls for increasing scientific knowledge and transferring marine technology to developing countries. This is compounded by a wider gap in marine literacy, meaning here students and local researchers across Indonesia's coastal communities still lack accessible tools to engage with marine biodiversity, which works against SDG 4 Target 4.7. A low-cost system with an educational interface is therefore needed to address both gaps.

## 1.3 Project Objectives

**Objective 1:** To automate plankton identification through the development of a web-based app using transfer learning for a locally Indonesian dataset.

**Objective 2:** To create a model for local plankton species by incorporating a data augmentation pipeline.

**Objective 3:** To develop a low-cost, real-time system with an interactive educational interface that adapts to Indonesian waters and amplifies the skills of communities in their environs.

## 1.4 Project Scope

### 1.4.1 System Scope

a. Adaptation to the Environment and Deployment on a Regional Basis

This system will be designed with the oceanography of the Indonesian seas in all 9 selected deployment areas. The project, in line with the most recent biogeographical studies, intentionally selects and allocates these identification regions into two main areas, Western and Eastern Indonesia, for Plankton Distribution Research and Identification, reflecting the oceanographic influence of the Indonesian Throughflow (ITF), locally known as Arlindo (Arus Lintas Indonesia), whose seasonal nutrient flux patterns directly shape regional plankton community composition and distribution (Horii et al., 2023; Tapia et al., 2022; Taufiqurrahman et al., 2020), to maximize coverage of the research's distribution. The data augmentation pipeline considers the changes due to the different conditions of Indonesia to incorporate accurately the changes in depth, light, sediment to plankton to season, to ensure enough variance to the model, as Duckworth (2025).

The process of developing and refining the model will involve the Indonesian National Research and Innovation Agency (BRIN, Badan Riset Inovasi Nasional) and ocean and plankton researchers. Such partners will bring regional expertise in plankton taxonomy, oceanography, and regional or local contextualization to tailor the models to specific local ocean conditions and prevailing plankton assemblages. With this approach, the system will be refined systematically and iteratively within the target regions to achieve ecological and functional alignment with Indonesia's blue economy objectives.

b. Transfer Learning-Based CNN Architecture

This system will use transfer learning based on modifications of pre-trained Convolutional Neural Network (CNN) models tailored to the identification of plankton species in Indonesia. Maracani et al. (2023) have shown the merits of the transfer learning strategy on in-domain datasets. The most appropriate base model selected for this system is EfficientNet-B0, chosen for its compound scaling method that balances network depth, width, and resolution, outperforming MobileNetV2 on imbalanced datasets with statistically significant macro-F1 advantages validated through McNemar's testing (Mandave & Patil, 2025). In the context of plankton-specific classification, ensemble approaches incorporating EfficientNet-based architectures have shown strong performance across multiple benchmark datasets, further validating its suitability for this task (Nanni et al., 2025). The models will be fine-tuned via progressive layer unfreezing, adjusting the pre-trained ImageNet weights to focus on the morphological features of Indonesian plankton. Ciranni et al. (2025) reported that achieved high accuracies on the WHOI22 dataset. This demonstrated the capability of transfer learning within resource-limited environments and the ability to continue performing exceptionally well on plankton classification tasks.

As stated, the in-domain transfer learning approach (pre-training on other plankton datasets before fine-tuning on target datasets) achieved a 3.2%

improvement in F1-score over out-of-domain approaches. This illustrates the value of using pre-training sources from relevant domains, following the guidelines outlined, which focus on plankton image classification tasks, achieving 89.3% precision on imbalanced datasets.

c. Data Processing and Augmentation Pipeline

The data processing module includes advanced preprocessing methods that compensate for poor image quality in Indonesian plankton collected under varying lighting conditions in highly turbid tropical waters. Images were resized to 224×224 pixels. Pixel values were normalized according to mean and standard deviation of ImageNet. Brightness was adjusted using ColorJitter to approximate or simulate the lighting variability expected in Indonesian underwater conditions.

To enlarge the training data and improve generalization, systematic data augmentation was applied. RandomResizedCrop (scale 0.75–1.0), RandomHorizontalFlip, RandomVerticalFlip (p=0.5), RandomRotation (±35°), ColorJitter (brightness=0.4, contrast=0.4, saturation=0.3), GaussianBlur (σ=0.1–2.0), and RandomErasing (p=0.20) were used to mimic the optical variability in Indonesian tropical waters and were selected according to the augmentation recommendations for plankton image classification tasks. For validation and testing, images were resized and center-cropped, then normalized using the same ImageNet parameters. Class-weighted Cross Entropy Loss was used to address the common class imbalance in datasets for marine biodiversity. This method, compute_class_weight('balanced'), weights the classes inversely to their frequencies to ensure that the rare species are overrepresented during training (Kyathanahally et al., 2021).

d. Model Performance Evaluation Metrics

Top-1, Top-3 and Top-5 accuracy would be employed for a thorough assessment of classification performance from the framework. Additionally, the framework will measure precision, recall and F1-score. Kyathanahally et al. (2021) demonstrated that macro-averaged F1-score is more appropriate than overall accuracy for imbalanced plankton datasets, as performance across all classes is weighted equally in this metric. During the evaluation, the framework will compute per-class precision, recall and F-scores for all plankton classes.

This framework utilizes confusion matrix analysis to evaluate the inter-relatedness between classifications of morphologically similar plankton species. Maracani et al. (2023) show confusion matrix visualization can reveal which copepod species are confused due to similarities in body shape, providing directionality for structuring data augmentation aimed at improving model performance. Within the stratified train-validation-test split, the test set is kept unseen during training, allowing evaluation to approximate how well the model generalizes to new, previously unseen Indonesian plankton data. The extent to which this separation was maintained in practice is discussed in Section 5.4. The practical viability of the web-based implementation will also be evaluated by tracking computational efficiency indicators. For example, inference time, memory footprint, and throughput.

e. Web-Based Application Architecture

This system employs a three-tier architecture for the user interface, inference engine, and database to enable timely plankton detection. The user interface will include an image upload interface that allows users to upload, process, and perform batch uploads. According to Yue et al. (2023), the EfficientNet-B0 computation enables real-time classification and can perform inference on standard web servers without a dedicated GPU.

Simultaneously, multiple users will be able to request web-based inference. To even out system load, the architecture will use request queuing and prioritize requests. This will be coupled with a responsive user experience. Within the database, the training datasets will be stored alongside the various model iterations to support reproducibility during training, along with user query logs, all in support of system development. By employing Duckworth (2025) methods, the interface will include educational touchpoints listing the top three species with the highest confidence scores and corresponding links to AlgaeBase and WoRMS, thus supporting SDG 4 Target 4.7. These touchpoints will also actively include the distribution maps of the identified species for both the Eastern and Western Indonesian waters.

### 1.4.2 User Scope

a. Target User Groups and Requirements

Three distinct user groups are served by the system, each with its own roles and access levels. Expert Users are marine researchers and taxonomists who can validate, modify, and comment on classification results. They need innovative tools that enable batch processing of large datasets and support temporal analysis to track and analyze changes in plankton populations. Expert Users help the system by annotating datasets and morphologically annotating datasets (Kyathanahally et al., 2021).

General Users include people involved in environmental research, students, and community members. This group of users employs the system for plankton identification and its capable of uploading images. Settings and classifications likewise remain fixed and cannot be altered by this group, though feedback may be submitted to the system.

Acting in a technical capacity, System Administrators are responsible for maintaining the deep learning model. These users analyze performance metrics and identify when retraining would be most effective, given newly expert-validated data, and are also responsible for selecting the training data used to prevent overfitting. The tiered system allows to maintain data integrity while also keeping the access open to the public.

b. Functional Capabilities and Performance Requirements

Plankton images can be uploaded by dragging and dropping the image files onto it or through the interface's file selection option. Image files have the following supported formats. There are JPG, JPEG, PNG and HEIC, which files outside this list are automatically converted to a compatible format. Top-3 species predictive rankings are displayed based on confidence score, including species name, confidence percentage, and designation badge (AI Confident, Expert Verified, or Pending). These badges provide external reference linkages to AlgaeBase and

WoRMS for the corresponding classification. Special system interface according to the user type General Users have a simple interface. Whereas Expert Users utilize a more advanced interface with the system enabling batch image processing, performance tracking, and queue management.

The results of the classification can be generated in PDF reports for further analysis and reporting. This allows Expert Users to export structured data for downstream research as well. For end users, the ability to filter for lower-confidence predictions is essential, since these can later be tested and verified. The function of the expert here becomes one of quality assurance. The strategies of prioritizing requests and server caching minimize the risk of server overload during peak periods while maintaining high system uptime and responsiveness.

c. Educational Interface and Learning Support

The education interface helps General Users and students acquire skills to identify different types of plankton. The system facilitates learning through the top-three species predictions on the results page, each accompanied by confidence scores and external reference linkages to AlgaeBase and the World Register of Marine Species (WoRMS), where users can further explore morphological details, ecological roles, and global distribution information of identified species.

In a study, Duckworth (2025) showed that active learning, along with immediate feedback, is a key characteristic of effective learning interfaces that help minimize misidentification among novices. The system allows educational users to elevate and refine their skills to levels that mimic the competency of a para-taxonomist. General Users and students are also educated through an active learning cycle that reinforces model misclassifications for validation by Expert Users. Classroom users are ensured equal and steady growth of their skills alongside the system.

## 1.5 Project Significance

### 1.5.1 Scientific Significance

This project helps close one of the existing gaps in the research on marine biodiversity. It aims to develop the first automated, web-based plankton classification system for Indonesian waters. Automated deep learning classification systems, as noted by Bachimanchi et al. (2023), can reduce the time spent identifying plankton by 87% compared to manual microscopy. This automated taxonomic identification can be performed at a level comparable to that of an expert manual classifier, thereby removing the challenge posed by limited taxonomic capacity.

For Indonesian waters, the system incorporates image enhancement algorithms to address the optical challenges of poorly contrasted, highly turbid tropical coastal waters characteristic of Indonesian marine environments. Owing to this advancement, automated identification of plankton in previously inaccessible tropical coastal and estuarine areas of Indonesian waters became possible. These regions cover the various environmental conditions the model should address for robust generalization across Indonesian waters. Working alongside local research institutes such as BRIN, this project also evaluates the applicability of global deep learning models across various biogeographical regions of the Indo-Pacific, thereby adding scientific and rigor.

### 1.5.2 Practical and Societal Impact

The web-based deployment model democratizes access to plankton identification tools and eliminates the need for specialized knowledge or high-cost equipment, enabling the assessment and identification of marine biodiversity in Indonesian waters. It supports students and practitioners of conservation and resource management in undertaking informed ecological decisions in the absence of formal training in taxonomy. The system builds user expertise from beginner to para-taxonomist levels by providing the top three species prediction results, linked to AlgaeBase and WoRMS.

By providing marine identification technology to one of the world's developing countries of over 17,500 islands, the system supports Indonesia's SDG 14 Target 14.a commitment, and by linking automated identification outputs to external scientific frameworks, it progresses SDG 4 Target 4.7. The model's ability to recognize plankton across different regional contexts supports the identification of anomalous compositional shifts that could signal the intrusion of potentially harmful algal blooms (Costa-Areglado et al., 2025). The model's lightweight nature also allows deployment on small boats and at community identification hubs to provide community-driven data to help manage marine protected areas and coastal development plans.

### 1.5.3 Economic Impact and Livelihood Enhancement

Plankton characterization technology can aid Indonesia's ecosystem-based coastal management. Identifying plankton can better inform the understanding of impacts on the foundation of the marine food web. Variations in plankton communities can positively or negatively impact fish productivity, and community-composition data gathered through systematic identification can inform, though not replace, expert-level decisions required for fisheries management and aquaculture planning.

In Indonesia, where communities rely on fishing and aquaculture, the introduction of an affordable, automated system for plankton identification removes an unnecessary cost barrier created by the high cost of manual taxonomy. This research aims to design an automated plankton identification system with high accuracy using transfer learning and data augmentation. The identification of plankton in different environmental contexts would provide the framework for ecosystem-based approaches to coastal management. It would assist in achieving SDG 14 Sustainable Development Goal (SDG) Target 14.a by providing science-based identification tools at an affordable cost for Indonesia's blue economy, enabling a broader range of technology transfer efforts.

## 1.6 Chapter Summary

In this chapter, the author lays the groundwork for an automated system to identify plankton in Indonesia. Manual taxonomy is costly, time-consuming, and requires highly specialized training. As a possible solution, a web-based deep learning approach automates plankton identification using EfficientNet-B0 transfer learning to build a custom data augmentation pipeline tailored to the optical variability of Indonesian tropical waters. This system is designed to support accurate, automated plankton identification across Indonesia's many tropical archipelagos.

Identification coverage is allocated across the Western and Eastern divisions in line with the oceanographic influence of the Indonesian Throughflow (ITF), known as Arlindo. This project establishes 3 levels of access and identification. These are Expert Users (phytoplankton researchers), General Users (students, environmental researchers, and community members), and System Administrators. To maintain ecological and regional consistency, the project works in collaboration with BRIN, Indonesian National Research and Innovation Agency. The educational interface integrates AlgaeBase and WoRMS for automated identification, allowing users to gradually advance toward competency equivalent to a para-taxonomist level.

Apart from technological advancements, the system directly supports SDG 14 (Life Below Water), specifically Target 14.a, by transferring low-cost marine identification technology to Indonesia, strengthening its blue economy. The system helps achieve SDG 4 (Quality Education), specifically Target 4.7, by providing learners with tools and skills related to marine biodiversity and sustainable development.