A Review on Phytoplankton Detection and Recognition in Freshwater Digital Microscopy Images Using Deep Learning Object Detector

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Abstract: *Phytoplankton are microscopic aquatic organisms playing a great role in freshwater ecosystems in terms of primary productivity, oxygen production, and nutrient cycling. Precise detection and recognition of phytoplankton species are crucial for water quality monitoring, ecosystem health assessment, and environmental change analysis. Conventional methods for identifying species using microscopy are slow, labor-intensive, and expert-centric, thereby limited as soon as scaling and real-time implementation are to be concerned. Nowadays, advances in artificial intelligence, particularly deep learning foundation object detection technologies, provide a substantial improvement on the automated analysis of biological and environmental images. This review article gives an overall view of deep learning object detectors in the context of the detection and recognition of phytoplankton in freshwater digital microscopy images. Since this study was conducted, new models have appeared, such as region-based convolutional neural networks (R-CNN), Faster R-CNN, You Only Look Once (YOLO), and Single Shot MultiBox Detector (SSD), with a brief examination of their architecture, advantages, and limitations on working with microscopic image data. The paper also argues on good signal preprocessing techniques, such as image enhancement, noise reduction, and segmentation tools, which, along with the restricted visibility in aquatic situations, help enhance the detection rate considerably.Moreover, in the context of phytoplankton imaging platform use, this article goes into a discussion of public datasets and the issues with annotations such as class imbalance, species overlapping and variation in shape. Evaluation metrics found in the literature-which include precision, recall, F1-Score, and mAP-are also briefly presented for comparison sake.The main challenges posed include limited labeled data, computational complexity, and generalization across different water bodies. Emerging future directions include light models for real-time monitoring, as well as knowledge transfer methods and the amalgamation of multimodal imaging. The main objective of this review is to dashboard an updated state of comprehension giving the present and future leaps in the settings of the deployment of object detectors attached to deep learning platforms to perform efficient and accurate phytoplankton-analyzing tasks at fresh water-based environments.*

Keywords: *Phytoplankton detection, Deep learning, Object detection, Freshwater microscopy, YOLO, Water quality monitoring*.

I. INTRODUCTION

The small, plant-like organisms known as phytoplankton form the basis of the food webs in water and also help to keep the balance in the freshwater ecosystem. Herein, these microorganisms do indeed account for most of the oxygen and carbon that affects the fact that trends within that population are mostly used as an indication of the quality of water and environmental health. This is why present studies rely on the sort of identification and monitoring of phytoplankton species without which any form of environmental assessment, climate research, or sustainable management of water resources would just be an adjunct to all other traditional or innovative methods. The conventional methodologies, however, have been focused heavily on manual analysis of phytoplankton under a microscope by experts in this sector. The use of these methods is cumbersome, time-consuming, subjectivity ridden & inconsistency laden, owing to human error and inter-observer variability [1]. With the rapid development in imaging technologies, digital microscopy has come forth as a great tool to capture high-resolution images of phytoplankton, thereby leaving open the development of the automated identification and analysis. Concurrently, the field of artificial intelligence, especially deep learning has embarked on expansive leaps in image processing tasks with acknowledgment across the board of its implementation across various domains like medical imaging, remote sensing, and environmental monitoring. Deep learning-based object detection models such as R-CNN, Faster R-CNN, YOLO (You Only Look Once), and SSD (Single Shot MultiBox Detector) are cited on account of their success in identifying and localizing objects within complex visual scenes. It has mounted up with heightened urgency not to mention the speed with which these models are fast becoming applicable to microscopic image analysis, which greatly reduces the emphasis on manual feature extraction in favor of learning features from raw data. Deep learning approaches are hence considered preferable concerning any automation, scalability, and accuracy for quick and trustable recognition of different phytoplankton species, even if obscured by complex and problematic imaging conditions. This being said, there still exist some constraints to their application such as the lack of annotated datasets, high inter-class similarity among species, variations in morphology, overlapping cells, and differences in imaging conditions, and illumination and magnification [2]. In addition thereto, computational time and the requirement of big training datasets stand as extra constraints in real-world implementation [3]. The main objective and purpose of this review entail the examination of object detection and recognition in freshwater phytoplankton detection via deep learning decisions directed tree classifiers. It presents a structured appraisal of any potential solutions from traditional and recent research work, a perfect platform to compare the models of state-of-the-art deep learning, and thus assess the datasets and preprocessing of the same that have been used. Evolutionary metrics whereby evaluation is focused largely make up a part of the script. The context of the review is to identify gaps that exist in earlier research as well as lay down forthcoming dimensions as promulgated by the emergence of lighter models in the scene of detection, transfer learning, data augmentation techniques, and real-time monitoring systems [4]. Basically, the review entwines the recent strides in thinking and research in ecology and deep learning applications to place deep learning on the appropriate footing in enhancing automated phytoplankton monitoring systems, aiming at providing better environmental sustainability and water quality. The figure 1 illustrates different freshwater phytoplankton genera such as *Aphanizomenon, Gymnodinium, Noctiluca, Nodularia,* and *Prorocentrum*, highlighting their diverse morphological structures observed under digital microscopy.

Figure 1: Representative Freshwater Phytoplankton Genera in Microscopy [7]

II. PHYTOPLANKTON AND THEIR ECOLOGICAL IMPORTANCE IN FRESHWATER SYSTEMS

Phytoplankton are microscopic free-swimming, free-floating primary-producing autotrophic organisms inhabiting freshwater environments like lakes, ponds, rivers, wetlands, and reservoirs, forming the base of the food web of aquatic life. This group may even feature several taxonomic groups, from diatoms (Bacillariophyta), green algae (Chlorophyta), cyanobacteria (blue-green algae), dinoflagellates, and euglenoids to those with distinctly different morphological and physiological traits. Despite their being microscopic in size, phytoplankton as a group play a quite oversized role in the stability and function of aquatic ecosystems [5]. By photosynthesizing, they utilize the sun, carbon dioxide, and other essential dissolved nutrients to skimp out substantial portions of the oxygen that forms the Earth's prevailing atmosphere and act as primary producers whose by-responsibilities encompass support for all subsequent NPCI higher trophic levels, including herbivorous zooplankton, fish larvae, aquatic invertebrates, and all aquatic zooplankton. Phytoplanktonic populations in freshwater systems are typically highly dynamic, changing fast in response to fluctuating environmental factors such as nutrient availability, temperature variations, light levels, pH concentration, and hydrology; hence, they are considered quite Virginian bio-indicators of ecosystem health and water quality [6]. Their species composition and abundance can directly be influenced by inputs of nutrients, mainly nitrogen and phosphorus, which are often brought into the aquatic environment by way of agricultural runoff and sewage discharge from people and industrial disposal. When these nutritent levels are raised above the necessary level, they can result in the eutrophication process whereby such phytoplankton have a high rate of proliferation which results in the creation of algal bloom, particularly those algae regarded as eventual threat to the system. Said blooms, in addition to degrading water quality immensely, reduce the availability of oxygen, block out penetration of sunlight, and affect functionality within the structure of the aquatic food webs, in addition to producing toxins which are harmful to the aquatic organisms as well as crops and human beings [7]. As an example, cyanobacterial species were also well screened for microcystins and other hepatotoxins, which seriously threaten drinking water sources and public health. Hence, a continuous phytoplankton dynamic monitoring system is required for the occasional discovery of such disturbances and the timely enforcement of water resource management strategies.

Phytoplankton, in addition to their roles in primary production and assessment of water quality, are essential actors in biogeochemical cycles on a global scale. Their role in carbon sequestration is pronounced. Through the processes of photosynthesis and the subsequent sinking of organic matter into the deeper layers of water, the biological carbon pump can help reduce atmospheric carbon dioxide levels, thus mitigating global warming. As well, in freshwater ecosystems, phytoplankton participate in key nutrient cycling processes: they absorb dissolved inorganic nutrients and release these into the environment through decomposition and zooplankton grazing [8]. This nutrient cycling sustains ecosystem productivity and supports the sustainability of aquatic habitats. However, phytoplankton community ecological balance tends to get quite upset by human-induced disturbances such as pollution, climate change, urbanization, and land-use changes, which can lead to changes in species composition and dominance of harmful species and bring in long-term degradation of freshwater biodiversity [9].

Phytoplankton diversity and abundance studies are essential from a scientific and monitoring perspective due to the useful information they offer with respect to ecological status, trophic conditions, and stressors affecting freshwater bodies. The traditional method of identification of phytoplankton using light microscopy has highly skilled taxonomists classify these organisms according to morphological variations such as cell shape, size, colony structure, pigmentation, and internal vegetative cells: and though such method is held in high esteem as being reliable, it is, however, time-consuming, labour intensive, and not fit for large scale monitoring [10]. The morphological similarity between species along with variations from environmental conditions results in misclassification and agreement on results. An ever-increasing demand for the real-time monitoring of water quality necessitates the growth of automated imaging and computational technologies for phytoplankton study.

In light of increased digital microscopy, the high-resolution imaging systems now picture the thorny phytoplankton details with extreme clarity that matches pictures taken within a controlled laboratory and ones from field biomonitored aquatic systems [11]. These digital images are rich sources of data harvested for computation. In recent years, machine learning and deep learning have emerged as dominating forces in automating phytoplankton detection and classification. These wild new deep learning methods offer a bedrock for certain heavily amorphous microphotographs compared to traditional image processing methods, using learn-high-do-presentation and hand-crafted features. This, in turn, is electrifying research on expanding observations and online analysis in the freshwater ecosystems [12].

Phytoplankton pathway, several problems still lie unshocked despite all technological aids. The main problem in this line lies in the over-diversity of phytos and the morphological variability that they affect (which may further complicate classification). Cells overlapping with each others, debris, and noise are present in microscopic images-undubiously, a considerable drawback to detection performance. Besides, the field suffers from huge gaps in well-annotated data sets. In turn, deep learning methodologies' formulation never seems to show the much-needed generalization in most varied regions and environmental conditions [13]. Variability in imageries includes the equipment, the magnification and lighting conditions, general inconsistency, amending model failures. Robust pre-processing measures, data augmenting strategies, along with any other advanced entity detection framework for handling complex visual patterns must be embedded.

Phytoplankton are popularly considered as the critical fish of freshwater as well as an index of environmental health and aspects of global climate changes. An important aspect of ecological importance that cuts across multiple disciplinary domains is the creation of landscapes for food, oxygen for the atmosphere, nutrient cycling, and carbon sequestration [14]. Escalation of environmental pressure exerted on freshwater systems has necessitated an automated and faster solution for monitoring. Subsequently, the integration of ecological science and modern computation, particularly based on deep learning workflow for image analysis, could represent the potentially revolutionary direction for refining accuracy, scalability, and efficiency in detecting and recognizing phytoplankton in freshwater environments.

III. TRADITIONAL METHODS FOR PHYTOPLANKTON DETECTION AND LIMITATIONS

On the methodological terms, the detection and recognition of phytoplankton in freshwater ecosystems are traditionally very much fraught with the manual microscopic examination and classical laboratory-based techniques, which have been in use in limnology, marine biology, and environmental monitoring for many decades. This technique often requires water collection from freshwater bodies. For this, lakes, rivers, and reservoirs are subjected to water sample collection within the container. Additives such as formalin or Lugol's solution would then be added to avoid any degradation of the biological material [15]. Following inoculation by such chemical agents, determinations of such samples are then carried out by a trained taxonomist-looking for the particular species of phytoplankton through their light microscopy despite identifying and sorting them up on the basis of morphological traits such as cell shape, size, color, internal structure, colony arrangement, pigmentation, etc. Standard identification keys and taxonomic guides are used for differentiating between species of the major groups of diatoms, green algae, cyanophytes, and dinoflagellates. In addition to direct microscopic observation, techniques such as sedimentation methods using Utermöhl chambers are applied to draw phytoplankton cells down to the lower department of a settling chamber for more accurate counting and classification [16]. Apart from the traditional methods, flow cytometry provides a quicker measure of physical and chemical characteristics of cells, e.g., size and fluorescence, although it lacks in consideration of morphological detail concerning microscopy. Determination of chlorophyll-a concentration is often used as an indirect method for estimating the phytoplankton biomass and productivity within the aquatic system. Certainly, these traditional methods have significantly benefited ecological monitoring, yet there are critical limitations that make them unsuitable for use in modern environmental monitoring [17]. The most significant limitation relates to the time-consuming and labor-intensive process of manual identification, which requires highly trained experts with a sound taxonomic knowledge. It may take hours or even days to analyze a high number of samples, making it-unfit for monitoring in real-time or on a large scale. Also, manual identification is very subjective, with the identification prowess of each observer weighing heavy in the functioning of the identification process, which sometimes can result in differing results and ideas of the same aspect and, as such, those results are neither concrete nor reproducible. The other critical drawback is finding difficulty in distinguishing morphologically similar species, all of which get more distinguishing especially under varying environmental conditions where cell shape and size may differ owing to nutrient availability, temperature, or other stressful factors [8]. This morphological plasticity often results in misinterpretation. In contrast, for detecting rare or low-abundance species that might still have considerable kinds of influence in ecological or toxicological terms, traditional methods can, in reality, not provide much information for digital imaging and machine learning, at least not overly much. Preservation itself causes morphology changes in the cell, further marking the problem to identify in an accurate fashion. Furthermore, manual observation is not feasible in continuous or high-frequency monitoring of water bodies, which has become more important in the context of fast environmental transition, climate variability, and bloom-activating harmful algal bloom. No automation in traditional workflow systems means that processing large data sets are slow and inefficient, especially for long-term ecological studies and big freshwater quality assessments. Even when it is feasible to use flow cytometry and chlorophyll-based measurements that are considered faster, they cannot match species-level classification requirements in ecological-in-depth analysis. Nonetheless, although traditional methods have forged the foundation on which aquatic ecological research lies, their limitations to fast-programmed scalability, precision, and, in some cases, subjectivity, have led to the application of computational methods. Indeed, this has led to an increased uptake of digital imaging and machine learning techniques for phytoplankton recognition in freshwater ecosystems, which are especially useful in deep learning-based object detection models [19]. Table 1 summarizes the commonly used manual and laboratory-based techniques such as light microscopy, sedimentation methods, flow cytometry, and chlorophyll-a estimation, highlighting their respective advantages in ecological studies as well as key limitations including time consumption, reliance on expert knowledge, low scalability, and inability to provide fully automated or real-time species-level classification.

Table 1: Traditional Methods for Phytoplankton Detection and Limitations

Method	Description	Advantages	Limitations	Outcome / Use
Light Microscopy	Manual observation of preserved water samples under microscope for species identification based on morphology	High taxonomic detail, widely used standard method	Time-consuming, requires expert knowledge, subjective errors	Species-level identification in lab settings
Sedimentation (Utermöhl Method)	Phytoplankton cells are allowed to settle in a chamber and counted under inverted microscope	Better concentration of cells, improved counting accuracy	Slow process, not suitable for real-time monitoring	Quantitative estimation of phytoplankton abundance
Flow Cytometry	Cells pass through laser beam to measure size, fluorescence, and complexity	Fast analysis, high-throughput processing	Limited morphological detail, expensive equipment	Biomass estimation and partial classification
Chlorophyll-a Measurement	Measures chlorophyll concentration as proxy for phytoplankton biomass	Simple, quick indicator of productivity	Does not provide species-level classification	Water quality and biomass estimation
Manual Taxonomic Identification	Identification using taxonomic keys and expert classification	High accuracy when done by experts	Highly subjective, inconsistent results	Ecological surveys and biodiversity studies
Chemical Preservation Methods	Use of chemicals like formalin or Lugol's iodine for sample storage before analysis	Preserves samples for later study	Alters cell morphology, may distort results	Long-term sample storage
Optical Counting Chambers	Use of specialized chambers for cell counting under microscope	Standardized counting method	Labor-intensive, slow analysis	Population density estimation

IV. DIGITAL MICROSCOPY IMAGING TECHNIQUES FOR PHYTOPLANKTON ANALYSIS

Applying digital microscopy imaging techniques to phytoplankton analysis comes with a pioneering supervisory approach that prescribes high-resolution imaging of live automatization for flowing digital information processing over microcosmic pictures of aquatic superiorites. Unlike the optical microscope as formerly known with unbiased visual tests and subjective assessments, the modification of digital microscopy brings with it advanced digital photography image capture devices, accompanied by high-definition point-and-shoot cameras and also automated high-speed scanning systems combined with computer image processing, all to translate digital data preservation in phytoplankton samples. This works to design and imitate a perfect platform for systematic recording and assessment of digital inflows from the freshwater environments positively altering the insufficiency and inconsistency of ecological appraisals [20]. Hence, the typical digital microscopy method involves the preparation of water samples obtained from aquatic ends at the moment of primary visibility by mounting them onto either a clean glass slide or a selected imaging vessel that is verified by automated microscopes that dangle with motorized stages and sophisticated high-resolution sensing means. Those modes are able to capture and stitch together numerous images at various focal depths and different x-y positions in total, to manufacture a complete digital mirror of the sample's morphology in its natural spatial distribution. A conceivable development of fine structure information of species would include alternatives like phase-contract microscopy, fluorescence microscopy, dark-field microscopy, and still other higher pixelistic schemes. Their usefulness towards improved illumination of transparent or low-contrast phytoplankton cells should be praised. For the phase-contrast regime, contrast in the image is increased by converting phase distortions in the light passing through a medium to variations in brightness. Hence, phase-contrast can be employed to visualize live phytoplankton without staining [21]. Fluorescence microscopy leverages the application of fluorescent dyes, or pigments like chlorophyll, to delineate particular cellular constituents enabling discrimination of species at the boundary of their biochemical purview. Dark field, as opposed to standard techniques, achieves closed-loop illumination via light hitting the sample plane at an oblique angle, so that the background becomes completely black while the specimen refracts light to the viewer's eye for heightened detail. In consonance with these, hyperspectral imaging and multispectral imaging seem to be highly effective in phytoplankton research, capturing information across numerous wavelengths of light for extreme specificity in analysis among multiple species. Such imaging techniques furnish great datasets suitable for advanced computational analysis including feature extraction, segmentation, and classification of phytoplankton community composition. Nonetheless, raw digital microscopy images often contain noise, artifacts, uneven illumination, and partly overlapping organisms, thus undermining an accurate analysis [22]. Therefore, digital work can be quite fruitful to such end for the creation of standard resolution data for the following analysis pipelines. The work mechanisms to enable more precise detection and classification of phytoplankton include developing distinct segmentation procedures that isolate individual cells from the everyday world of cluttered background. The techniques of digital microscopy integrated into automated imaging systems have also served to induce installation of high-throughput platforms to process a large volume of samples within short periods, thus making them useful for continuous environmental monitoring and early detection of harmful algal bloom. However, these tools still face formidable challenges; large equipment costs, large data storage requirements, and variable imaging conditions are only some of those. Moreover, the complexity of natural water samples in existing marine environments, characterized by the presence of debris, suspended particles, and several overlapping organisms, presents yet another formidable hindrance to the clean identification of these beings. Use of digital microscopy in advance alone is hence not likely to bring reliable results during fully auto-analyses of phytoplankton, with the only solution increasing being in use of artificial intelligence, specifically machine learning and deep learning as additives to this portion that may retrofit the specter of algoane from drawing back less and giving altitude to automatic differently for the imprecise reliance as currently. Numerous studies augment phytoplankton classification based on convolutional neural networks and object detection models in digital microscopic images; hence, at a very high precision rate, these techniques can accurately decipher the identity of phytoplankton species at the higher scale. Generally, digital microscopy is regarded as a fundamental transition in aquatic ecology, casting a bridge between traditional manual observation and advanced machine-learning-based configuration to be the solid foundation of on-demand, scalable, and automated phytoplankton monitoring in freshwater ecosystems.

V. DEEP LEARNING-BASED OBJECT DETECTION MODELS FOR MICROSCOPY IMAGES

Deep learning-based object detectors have transformed the field of image analysis by providing automated detection, localization, and classification of objects in complex visual scenes and have therefore greatly improved phytoplankton recognition in freshwater ecosystems using the application of microscopy. Unlike the painstaking, traditional image-processing methods requiring handcrafted features, such as shape descriptors, texture analysis, or threshold-based segmentation, deep learning models automatically learn hierarchical feature representations straight from raw image data; consequently, they are highly effective in dealing with complex, noisy, and high-variability microscopic environments. Referring to architectures, there are numerous region-based convolutional neural networks (R-CNN), Fast R-CNN, Faster R-CNN, You Only Look Once (YOLO), and Single Shot MultiBox Detector (SSD), with different trade-offs in accuracy and computational efficiency [23]. R-CNN and its variated methodologies introduced region proposal networks where potential object regions were first to be identified before being classified and ensured high detection accuracy, but those had not paced to faster speed with multi-stage pipelines. Faster R-CNN employed a significant upgrade in the aforementioned operation by embedding region propose generation into the network itself, resulting in a good balance between high accuracy and considerable efficiencies, thus proving apt for more involved phytoplankton identification tasks in which precision is critical. By contrast, with the value of combining real-time object detection and treating detection as a single regression problem-to directly predetect bounding boxes and class probabilities from full images in one forward pass-that has brought YOLO-based models to their current fame. This perspective would make them quite useful in larger or real-time water quality-monitoring systems where speed is crucial [24]. This configuration offers a nice_mixture between accuracy and speed by detecting objects at different scales within feature maps from various levels of resolution, thus extending usability in detecting phytoplankton species of varying size and shape. In microscopic images, their real difficulty results from organisms that overlap one another, creating low contrast and very uneven illumination, and looking quite like morphological neighbors. So many workers therefore import contemporary, high-profileed backbone networks; their ResNet, VGGNet, DenseNet to enhance feature extraction capacity, enabling the models to capture casually but complex structural details of phytoplankton cells. Transfer learning has become one of the strategies widely adopted, with ImageNet pre-trained models being fine-tuned on phytoplankton-specific datasets in order to facilitate both shortening of training time and accentuating performance on mostly unknown phytoplankton datasets [25]. Last of all, attention mechanisms have been employed to boost model focus on significant parts of the microscopic image for high recognition rates in a muddled background. Even with these victories, deep learning-based object detectors are still faced with issues such as heavy computational burdens, dependence on large annotated datasets, and poor generalizability across numerous kinds of imaging conditions and/or aquatic environments. Lightweight models and possibly optimized architectures are currently being studied as deployment solutions for edge devices, as well as portable imaging systems, to better handle real-time field applications. Overall, these deep learning-based object-detection models are a robust and dynamic advance into the automatic detection of phytoplankton in microscopy, greatly outperforming the conventional methods in terms of speed, accuracy, and scalability and providing the foundation for smart environmental-monitoring systems.

VI. DATASETS AND PREPROCESSING TECHNIQUES FOR PHYTOPLANKTON DETECTION

Datasets and preprocessing techniques lie at the core of deep learning-based sensing systems targeting phytoplankton. It is a truism that the size, diversity and representativity of the training data directly influence the accuracy, generalization capability and robustness of the model in the real world. The typical phytoplankton dataset used for training is the production from freshwater digital microscopy images obtained from lakes, rivers, and controlled laboratory laboratory-induced environments, so that water specimens are observed under different magnifications and lighting conditions using high-resolution imaging systems. Such datasets contain a variety of classes of phytoplankton, such as diatoms, green algae, cyanobacteria, and dinoflagellates-all breeds of wide morphological variability, thereby posing a tremendous challenge on the construction and annotation of the datasets [21]. Within the domain, the big, well-known datasets are relatively few in number, whereas the majority of researchers have resorted to forms of kindred datasets for which manual annotation by the domain scientists is the only way out, so a lot of labors are artifacted in order to mark either an entire phytoplankton cell by bounding the boxes or with segmentation masks. Annotation most often happens via tools such as LabelImg, VGG Image Annotator (VIA), or other such microscopic annotations, but this takes enormous time and a lot of human error occurs especially because of contiguity from the extreme tinyness to overlap among organisms. One of the biggest rationales with phytoplankton datasets is class imbalance whereby, as a result of overrepresentation by some species, minor species, which may very well be rare or toxic and could form a threat in the monitored areas, are rather poorly represented, generating training bias and subsequently reducing the prediction power for low-count-term minority classes. To eliminate the aforementioned inexistence, a number of preprocessing steps are effectuated for enhancement of image quality and production of better feature extractors long before inputs are supplied to the model. The usual preprocessing steps include image resizing to the same dimensions, pixel intensity value normalization, and contrast improvement using his’s-gram equalization, and noise filtering by workouts such as Gaussian or median filtering. Background subtraction techniques are applied to remove unwanted particles and improve phytoplankton cell visibility [25]. Segmentation techniques such as thresholding, watershed algorithms, and edge detection perform the operation of detaching isolated organisms from a mess of microscopic backgrounds. Data augmentation is fine. Required for model generalization, this is the crucial and easy-to-train augmenting with varying transformations, e.g., rotation, flipping, scaling, cropping, brightness adjustment, and elastic deformation, which simulate variations under real-world imaging conditions. On the other hand, there is an interesting prospect of synthetic data created by generative adversarial networks (GAN), as such data will provide a secure pathway to remedy the scarcity of real identified phytoplankton images, in favor of artifacts showing training diversity. What remains is annotation refinement, required to fix erroneous or inconsistent labels that would only lower the quality of the dataset and, thus, the whole model training process. Standard validation datasets must be distributed making sure that much observation goes into creating three, i.e., training sets, validation sets, and testing sets. The splitting process ensures data leakage avoidance and unbiased evaluation. Despite these successes, the absence of large-scale, standardized and publicly accessible phytoplankton datasets remains a major barrier for successful deep learning model development. Variability in imaging equipment, environmental conditions, and sampling locations further complicates dataset standardization and model generalization across different freshwater ecosystems. Hence, future research is aimed at creating vast, diverse, and annotated benchmark datasets, as well as state-of-the-art preprocessing pipelines that can cope with real-world variability. To sum up, datasets and preprocessing techniques underlie the solid structure of deep learning-based phytoplankton detection systems, with improvements in this area thereby ensuring robust automatic monitoring for freshwater ecosystems going forward. Table 2 summarizes existing studies on phytoplankton detection, highlighting the use of deep learning models (such as CNNs and YOLO variants) for species classification, counting, and monitoring in marine environments, along with their reported accuracy and key limitations.

Table 2: Comparative Analysis of Existing Studies

Ref. No.	Method / Focus	Key Findings / Result	Limitations
[2]	Deep learning plankton classification	Improved species classification and microbial analysis	Requires large labeled datasets
[3]	Computer vision + DL monitoring	Effective biological image quantification	General biological focus, not phytoplankton-specific
[4]	Systematic review (microscopy DL)	Shows strong DL potential in microscopy analysis	Limited real-world deployment studies
[5]	Imaging system (bright-field & fluorescence)	Enhanced phytoplankton image acquisition	High equipment complexity
[6]	Vision transformers (PlankFormer)	High accuracy instance segmentation	Computationally expensive
[7]	ML for trophic status prediction	Links phytoplankton indicators with water quality	Not image-based detection
[8]	Attention-based DL model	Improved zooplankton classification accuracy	Focused on zooplankton, not phytoplankton
[9]	Fluorescence detection system	High sensitivity algal identification	Requires specialized lab setup
[10]	Remote sensing + PCR	Detects toxic cyanobacteria distribution	Not purely image-based DL
[11]	Morphometric trait extraction	Automated plankton feature analysis	Limited classification capability
[12]	Machine vision microplastic detection	Rapid quantitative analysis system	Not directly phytoplankton-focused
[13]	Raman spectroscopy + DL	Accurate harmful algae classification	High-cost instrumentation
[14]	Lensless holography imaging	Improved underwater microorganism reconstruction	Complex reconstruction process
[15]	DL-based stomach content analysis	Automated marine biological classification	Domain-specific application
[16]	Chlorophyll fluorescence DL model	Effective algae classification	Limited dataset diversity
[17]	Explainable DL holography	Improved microplastic detection interpretability	Not phytoplankton-specific
[18]	ML/DL water quality estimation	Accurate environmental monitoring	Indirect phytoplankton relation
[19]	Satellite + Gaussian models	Ocean front detection	Large-scale not microscopic
[20]	Ecotoxicological diatom study	Shows pollutant impact on diatoms	No automated detection model
[21]	DL object detection (red tide)	Accurate harmful phytoplankton detection	Limited to red tide species
[22]	Deep learning classification	Improved harmful algae classification	Dataset constraints
[23]	DL on ballast water microalgae	High detection accuracy in marine systems	Requires staining process
[24]	Fossil diatom DL detection	Effective automated counting system	Affected by morphological variation

A. CHALLENGES, RESEARCH GAPS

While significant progress has been achieved in the field of phytoplankton detection and recognition using deep learning applied to freshwater digital microscopy images, there still exist critical challenges and gaps in research that inhibit their widespread adoption and deployment in real environments. First and foremost, one main hurdle in this regard is the scarcity of large-scale, high-quality annotated datasets; so far, the majority of the existing datasets are either limited or localized while being manually marked, rendering generalization a tough task for such models across disparate freshwater habitats. Another critical issue involves the high levels of morphological similarity between the different phytoplankton species, which often results in misclassification, particularly if overlaid or in densely populated microscopic images. Due to variations in imaging conditions such as lighting, magnification, and noise, the model performance is severely deteriorated and its robustness decreased. Concerns with computational complexity further arise with many state-of-the-art object detection models that require heavy processing power for their deployment in real-time or with portable/field-based devices. This is further intensified by class imbalance in the datasets, where some species are grossly underrepresented, resulting in biased learning and poor detection of rare but ecologically important species. Among the significant research lacunae is a lack of any sort of standardized benchmarks or evaluation protocols that allow a fair comparison of various models. The modest input of marine biology domain knowledge in deep learning has hitherto restrained interpretability and ecological relevance. The way forward to address these challenges presupposes that enhanced robustness of datasets, less resource-intensive ACNN architecture, well-established annotation strategies, and cross-disciplinary cooperation must be undertaken as a joint effort to improve the accuracy and usage of automated phytoplankton detection systems.

VII. CONCLUSION AND FUTURE DIRECTIONS

This paper reviews the application of deep learning-based object detection techniques for the detection and recognition of phytoplankton for freshwater digital microscopy images. It is evident by the results reviewed here that recent deep learning models, such as R-CNN, Faster R-CNN, YOLO, and SSD, provide immense help in increasing the accuracy, automation, and efficiency of phytoplankton identification concerning the manual and semi-automated methods. Using these models, the working time in the analysis of complex microscopic images can be reduced and sustained with large-scale environmental surveillance minimising human intervention. Despite the remarkable technological advancements, their practical applications must be tempered as reflected in limited annotated datasets, greater computational requirements, class imbalances, and less generalization in the limnetic environment of diverse aqua-milieus. In the future, researchers have to work on the development of light and energy-efficient deep learning models that could decisively find real-time field-based applications.

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