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Detection and Classification of Harmful Algae using Machine Learning - A Review

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ABSTRACT
This research addresses the escalating issue of harmful algal blooms (HABs) by introducing advanced automated detection algorithms, such as YOLOv3, YOLOv4, YOLOv5, Cyanobacterial Algal Bloom Detection Algorithm, and AlgaeNet. The study delves into specific harmful algae types, exploring their ecological implications. It discusses each detection method's advantages and limitations, emphasizing factors like speed, accuracy, and computational demands. Practical guidelines for water sample collection and processing are provided, highlighting the capability to classify algae post-detection for a comprehensive understanding of algal communities. Moreover, the study underscores the potential impact of harmful algal blooms on the environment, human health, and economic sectors, emphasizing the urgency for advanced monitoring techniques. The integration of machine learning and remote sensing technologies in algae classification not only expedites the detection process but also opens avenues for real-time decision-making and proactive management of algal bloom events. This research serves as a pivotal step towards a holistic approach to mitigating the detrimental effects of HABs, fostering sustainable aquatic ecosystems and safeguarding communities worldwide.

Keywords: Harmful Algal Blooms (HABs), automated detection algorithms, algae classification, remote sensing

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I. INTRODUCTION

Algal bloom is a phenomenon in which there is a rapid increase in the population of phytoplankton, also known as algae, in a water body such as lake, river or sea. It is often recognized by the discoloration in the water from the algae's pigments. Algal blooms are the result of a nutrient, like nitrogen or phosphorus from various sources (for example fertilizer runoff or other forms of nutrient pollution), entering the aquatic system and causing excessive growth of algae. An algal bloom affects the whole ecosystem. Algal and bacterial blooms have persistently contributed to mass extinctions driven by global warming in the geologic past. Earlier malwares were easier to detect as they had some specific type of signature and had a single process, thus we classify these kinds of malwares into traditional malwares also referred to as simple malwares. These traditional malwares are less sophisticated and are easy to detect. Whereas the next generation malwares are highly sophisticated and use various process and methods to hide itself from detection and pretends to be a benign or legitimate software or code.

Harmful algal bloom (HAB) is a toxic algal bloom that has a detrimental impact on the environment, human health, and the economy. The mortality of marine species is one of the environmental consequences. Human health consequences include health deterioration as a result of consuming contaminated seafood, which can result in serious disease or death. Economic consequences include the destruction of tourist attractions due to the inability to conduct activities such as fishing and snorkeling, as well as the deterioration of the aquaculture sector due to massive fish deaths. To safeguard the user and the companies from these attacks and prevent financial and social losses, malware detection is a very important process. The process of detecting and classifying various malwares into its families, analyzing them based on their signatures and behaviors is generally referred to as malware analysis. The traditional or early malware could be easily detected using signature or heuristic based approaches. But these approaches have many limitations, as they cannot detect the mutated or self-evolving next generation malwares which are usually unknown and new. With the present world, where rapid development is seen in several domains like Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and so on, has led to the progress of evasive malwares which can trick the detection systems and are highly sophisticated and self-evolving.

Monitoring of hazardous phytoplankton is critical for the preservation of the aquatic biological environment. Traditional algae monitoring methods, which are time-consuming, expensive, and limited in practice, necessitate people with extensive experience in algae species.

Previous methods for algae monitoring rely on professionals with considerable experience of professional training and practical experimental experience in algae identification, which involves a time-consuming, high-cost, and labor-intensive process to inspect a limited number of samples. As a result, a number of automatic identification algorithms for algal photos have been presented and have made significant progress with the maturation of associated technology.

The most commonly used early monitoring methods are to sample and process water, and then observe the distribution of algae in the water samples with naked eyes using microscopes and other laboratory instruments; the proposed method in this work can be used to automatically recognize and classify microscopic images of algae and identify the harmful algae images in samples, saving a significant amount of time and effort.

II. TYPES OF HARMFUL ALGAE

Harmful algal blooms (HABs) harm the marine environment and public health. This in-depth research explores the prevalence, nature, and possible harmful effects of selected algae species associated with HABs. Acanthosphaera, Nostoc, Coelosphaerium, Bacillariophyta (Diatoms), Crococcus, Coccomonas, Cosmerium, Luojaomen, Oscillatoria, Merismopedia, Pandorina, Volvox, and Dinophyta are the families under inspection. The objective of this project is to gain a better knowledge of these species' ecological implications in order to establish appropriate research and management strategies for detection and classification.

Acanthosphaera: Acanthosphaera is a type of marine microorganism from the Radiolaria group, recognized for its complex mineral skeletons and spherical forms, commonly present in plankton within oceanic environments.

Nostoc: Nostoc is a cyanobacterial genus with the ability to fix nitrogen, forming gelatinous colonies. These microorganisms are essential in nitrogen cycling and can be found in diverse habitats such as soil and freshwater.

Coelosphaerium: Coelosphaerium, a cyanobacterial genus, typically forms colonies with spherical shapes. These photosynthetic microorganisms are significant contributors to aquatic ecosystems, generating oxygen and serving as primary producers.

Bacillariophyta (Diatoms): Diatoms, a major algal group within the Bacillariophyta division, are microscopic, unicellular organisms with intricate silica cell walls. They play a critical role in global oxygen production and carbon cycling in aquatic ecosystems.

Crococcus: Crococcus, a cyanobacterial genus known for its spherical or ovoid cells, is commonly found in freshwater environments, contributing to nutrient cycling and ecological balance.

Coccomonas: Coccomonas, a genus of small, unicellular flagellates within the Cryptophyta group, is found in aquatic environments, playing a role in the microbial food web.

Cosmerium: Cosmerium, a green algae genus forming colonies of cells embedded in a gelatinous matrix, is prevalent in freshwater habitats, influencing the ecological dynamics of aquatic ecosystems.

Luojaomen: The term "Luojaomen" lacks recognition in biological literature, requiring additional context for accurate information.

Oscillatoria: Oscillatoria, a filamentous cyanobacterial genus with oscillating movement, is widespread in various aquatic habitats, forming mats or filaments in nutrient-rich conditions.

Merismopedia: Merismopedia, a genus of colonial cyanobacteria with flattened, disk-like colonies, is commonly found in freshwater environments.

Pandorina: Pandorina, a green algae genus forming spherical colonies of a fixed cell number, is a notable example of multicellular organization among algae.

Volvox: Volvox, a green algae genus known for its colonial structure with numerous cells arranged in a hollow sphere, exhibits simple multicellularity and is studied for insights into evolutionary transitions to multicellular life.

Dinophyta: Dinophyta, or dinoflagellates, constitute a diverse group of unicellular algae with a distinctive two-flagella structure. Abundant in marine environments, they play a crucial role in marine food webs, with some exhibiting bioluminescence

III. DETECTION METHODS

III.1 YOLOv3

Due to its well-known real-time object identification capabilities, the YOLOv3 model is a good fit for applications that operate in dynamic contexts. It efficiently detects objects in photos and videos by striking a balance between speed and precision. Its quick frame processing speed is one of its main advantages, which makes it appropriate in situations when prompt detection is essential. Nevertheless, YOLOv3's performance might not be on par with that of later iterations, and it might have trouble correctly identifying tiny objects. Furthermore, even while it achieves a good balance, there is still opportunity for accuracy enhancement, particularly for tasks demanding precision. YOLOv3's benefits include real-time object detection and Processing frames in a dynamic context efficiently. YOLOv3's limitations include difficulties detecting small objects and lower accuracy than newer versions.

III.2 YOLOv4

YOLOv4, which builds on the advantages of YOLOv3, offers significant enhancements in speed, accuracy, and the capacity to identify smaller objects. With the addition of sophisticated features like CSPNet and PANet, this version can handle more complicated situations with greater ease. When pinpoint accuracy and the ability to identify small objects are critical, YOLOv4 performs exceptionally well. Its processing demands, however, could provide difficulties; for best results, sophisticated gear is needed. The improved accuracy and extra capabilities of YOLOv4 make it an appealing option for applications that value precision, even with this drawback. The advantages of this is that it has increased speed and accuracy and improved capacity to identify tiny items and the incorporation of sophisticated features like PANet and CSPNet. However, a limitation of this model would be that it requires High computational demands that could necessitate powerful gear.

III.3 YOLOv5

The YOLOv5 model brings even more improvements in speed and accuracy. Faster processing times are facilitated by its efficient training and inference capabilities, which stem from its simplified architecture. For users used to this deep learning library, YOLOv5 offers flexibility by utilizing the features of the PyTorch framework. This version performs better than its predecessors and is well suited for real-time object detection jobs. Its need on PyTorch, however, can be a drawback for those used to other deep learning frameworks. The upside of YOLOv5 is Cutting-edge speed and accuracy and Effective architecture for inference and training. The downside being the difficulty faced by users who are used to other frameworks.

III.4 Cyanobacterial algal bloom detection algorithm

Three stages comprise the cyanobacterial algal bloom detection algorithm: segmentation, extraction of the water body, and estimation of the algal bloom. Using an agglomerative clustering technique, super pixels are grouped during the segmentation phase in order to maximize the likelihood of different surface categories while taking color, texture, and contextual factors into account. This technique uses super pixel grouping to successfully limit entropy at the pixel level. The next step is the extraction of water bodies from the segmented image. To do this, a hybrid image segmentation approach is used, which combines inertial features detected by camera inertial sensors with visual features from the camera. Lastly, what sets the algal bloom estimating phase apart from many other approaches now in use is its complete lack of machine learning. The percentage of algae in the boxed areas of photos is calculated by this method.

III.4.1 Benefits

The three-phase structure of the method ensures computational efficiency by streamlining the algal bloom identification process.

The technique can lower the computational resources needed for implementation by operating without the requirement for sophisticated machine learning models.

The algorithm's ability to handle RGB photos from a variety of sources, such as smartphones, the Internet, and unmanned aerial vehicles (UAVs), improves its flexibility in a range of data collection situations.

III.4.2 Restrictions

The algorithm's performance is not fully evaluated in the study that is being given, nor is its applicability in various environmental settings or with a variety of datasets well appraised.

: It is noted that the algorithm is used to identify whether cyanobacterial algal blooms are present or absent, which may restrict its capacity to

offer precise details regarding the scope or intensity of the blooms.
Although the algorithm's robustness in handling noisy or low-resolution data is not specifically addressed in the context given, its performance may be impacted by the quality of the input photos.

III.5 AlgaeNet

This method detects floating green algae using satellite remote sensing, specifically merging optical MODIS pictures with synthetic aperture radar (SAR) data, with an emphasis on Ulva prolifera (U. prolifera). MODIS optical images provide broad coverage and frequent data collecting, allowing for the study and forecast of algal blooms. However, the constraints of intermediate resolution may result in inaccuracies in the extraction of algal biomass. SAR offers images of sea surface roughness that show floating algae as bright patches due to its superior spatial resolution and all-weather capability. Deep learning (DL) facilitates the integration of SAR and MODIS data, allowing for effective fusion of information gathered by both sensors. The DL network is intended to extract information about U. prolifera from optical and SAR pictures, overcoming the limits of standard methods for combining the two data sources. The floating and submerged algae ratio (FS ratio) is used to determine the life phases of U. prolifera and to evaluate and minimize the underestimate of algae in coarse-resolution optical images. The benefits include the synergy of optical and SAR data, which provides a more comprehensive view of algal blooms, as well as the potential for life stage estimation. However, because of the temporal coverage constraints of SAR data, limitations may develop, and the performance of the DL network would need to be thoroughly evaluated across varied datasets and environmental situations.

III.5.1 Advantages

The approach efficiently combines optical and SAR data, leveraging each sensor's strengths to improve algal detection accuracy.
Using DL allows the model to understand complicated patterns and correlations between optical and SAR data, potentially enhancing detection performance.
The method uses the floating and submerged algae ratio (FS ratio) to estimate the life stages of U. prolifera, offering important ecological insights.

III.5.2 Limitations

When compared to optical sensors, SAR has limited temporal coverage, potentially limiting continuous monitoring of algal blooms.
To achieve generalizability and robustness, the performance of the DL network must be rigorously validated across multiple datasets.
The accuracy of algae detection is dependent on the quality and consistency of the input data, and variations in environmental circumstances may have an impact on performance.

IV. SAMPLING AND SAMPLE PROCESSING

When collecting water samples for the purpose of detecting algal blooms, some additional measures must be made to ensure the preservation and analysis of algae-related data. Here are some particular instructions for gathering and preparing water samples for algal bloom analysis.

IV.1 Algal Bloom Detection Collection

Select Appropriate Locations: Select sampling locations based on known or suspected algal bloom occurrences. This could include discolored patches, increased turbidity, or reports of hazardous algal blooms (HABs). Vertical profiling: Collect samples at various depths to determine the vertical distribution of algae inside the water column, as algal blooms can vary in space.

IV.2 Algae Analysis Preservation

To retain the cellular structure of the algae, add fixatives such as Lugol's iodine or formaldehyde. Lugol's iodine is often used to preserve phytoplankton cells, allowing them to be identified and counted later under a microscope. Avoid Autolysis: Process samples as soon as possible to avoid autolysis (self-digestion) of algal cells, which can occur if samples are left unprotected for too long.

IV.3 Algae Analysis Sample Handling

Avoid Agitation: Avoid agitation during sample collection and handling to avoid breaking fragile algal cells, particularly if microscopic analysis is planned. Gentle mixing is required for composite samples to obtain a representative sample without injuring algal cells.

IV.4 Algae Analysis Storage-Refrigeration

Store samples at 4°C to slow down biological processes and preserve the integrity of algal cells. Short-Term Storage: Analyze samples as quickly as possible to achieve accurate cell counts and avoid algal abundance variations caused by storage.

IV.5 Algae Analysis Documentation

Algal Species: If feasible, document the main algal species. This data can be useful in understanding the specific dynamics of the algal bloom. Details of

Microscopic Analysis: If the samples are for microscopic examination, keep track of the magnification employed, the volume of the counting chamber, and any dilutions made.

IV.6 Algae Analysis Transportation
Take precautions to avoid sample agitation during shipping, as severe shaking can compromise the integrity of fragile algal cells. If a laboratory study is not performed on-site, samples should be delivered to the laboratory as soon as possible to avoid changes in algal community structure.

IV.7 Algae Analysis Quality Control
Perform duplicate cell counts to ensure analysis precision, especially if the sample volume is low. If samples are sent to a laboratory for analysis, offer specific directions on the type of analysis required (e.g., cell counts, identification of hazardous species).

IV.8 Safety Considerations
As the goal is to find dangerous algae species that produce toxins, ensure that samples are handled with adequate safety precautions and consider sending them to a toxin analysis laboratory.

V. DATA ANALYSIS

Understanding the intricate dynamics of toxic algal blooms is mostly dependent on data analysis, which offers important insights into species identification, toxin concentrations, and general bloom patterns. Data analysis in the context of hazardous algae detection is a complex process that includes interpreting information from different detection techniques, from sophisticated molecular techniques and remote sensing technologies to conventional microscopy.

V.1 Interpreting Microscopic Data
Specific species identification is made possible by microscopic methods like light and electron microscopy, which provide a close-up view of individual algae cells. These techniques yield data on cell morphology, size, and organization that enable researchers to distinguish between several dangerous algae species. To measure cell density and evaluate the spatial distribution of algal cells in a water sample, image analysis software is frequently used. Through the use of such microscopic data, researchers are able to comprehend the structure and composition of algae populations within a particular ecosystem.

V.2 Molecular Data Analysis
Molecular methods, such as Polymerase Chain Reaction (PCR), are used to investigate the genetic markers of toxic algae. With this method, it is possible to identify species and identify certain genes linked to the generation of toxins. By comparing genetic sequences to reference databases, PCR data processing enables precise algal species classification. Furthermore, toxin gene abundance can be estimated via quantitative polymerase chain reaction, or qPCR, which offers information on possible toxin concentrations. The genetic variety and possible toxicity of hazardous algae are better understood thanks to data produced by molecular analysis.

V.3 Remote Sensing Data Interpretation
Using spectral analysis and satellite data, remote sensing technologies offer a more comprehensive spatial view of dangerous algal blooms. Chlorophyll-a, a pigment that indicates the presence of algae, has spectral characteristics that can be analyzed in order to interpret data from remote sensing. Quantitative data, such as the amounts of chlorophyll-a, is extracted from satellite photos using algorithms. Tools from Geographic Information Systems (GIS) improve the spatial investigation of the distribution of algal blooms. Researchers can support monitoring and management efforts by generating thorough spatiotemporal maps of harmful algal blooms through the assimilation of these datasets.

V.4 Statistical Approaches
Statistical methods form the backbone of data analysis in harmful algae detection. These approaches are employed to identify trends, patterns, and anomalies in the collected data. Time-series analysis enables the detection of temporal variations in algal bloom dynamics, while spatial analysis assesses the distribution patterns across different locations. Regression analysis may be applied to explore relationships between environmental variables and algal bloom occurrences. These statistical tools enhance our understanding of the factors influencing bloom development and contribute to the development of predictive models.

V.5 Machine Learning Applications
The foundation of data analysis for dangerous algae detection is statistical methodologies. These methods are used to find patterns, trends, and anomalies in the data that has been gathered. While spatial analysis evaluates the distribution patterns across various areas, time-series analysis allows the detection of temporal differences in algal bloom dynamics. Regression analysis can be used to investigate the connections between environmental factors and the incidence of algal blooms. These statistical methods aid in the creation

of predictive models and improve our knowledge of the variables affecting bloom development.

V.6 Integration for Deeper Understanding

In practice, a comprehensive approach to data analysis in the detection of toxic algal requires the integration of information from numerous sources. Data from microscopic, molecular, and remote sensing sensors, as well as environmental variables, are combined to provide a full picture of algal bloom dynamics. Integration improves species identification accuracy, refines toxin concentration estimations, and provides a more nuanced perspective of bloom dynamics. This comprehensive research is critical for designing effective management methods that allow for early actions to lessen the environmental and health effects of toxic algal blooms.

In conclusion, data analysis is the key to understanding dangerous algal blooms, converting raw data into meaningful insights. Researchers can uncover the complexity of algal bloom dynamics by combining microscopic, molecular, and remote sensing data with statistical and machine learning approaches. As technology progresses, refining data analytic methodologies will be critical for staying ahead of developing difficulties, eventually leading to more effective ways for detecting, monitoring, and managing hazardous algae in aquatic ecosystems.

VI. CASE STUDIES

VI.1 Monitoring Harmful Algal Blooms in Lake Erie Using Remote Sensing

A study in Lake Erie used remote sensing techniques, including satellite-based monitoring, to detect and monitor harmful algal blooms (HABs). The researchers used high resolution satellite data to locate and measure the extent of the lake's cyanobacterial blooms. The findings demonstrated a link between nutrient runoff and the presence of HABs, giving important information for water management methods. The study revealed remote sensing's usefulness in delivering timely and large-scale information on HABs, allowing for preventative interventions to mitigate potential environmental and public health implications. The learnt lesson stresses the significance of using remote sensing technologies into water quality management for early identification and informed decision-making.

VI.2 Deep Learning for Algal Bloom Detection in Coastal Regions

A team successfully used deep learning approaches for autonomous algae detection in a coastal location plagued by periodic algal blooms. A convolutional neural network (CNN) trained on a heterogeneous collection of multispectral satellite pictures was used in the study. The deep learning model accurately identified distinct algae species and estimated bloom intensity. The results demonstrated the effectiveness of deep learning in automating the detection procedure, allowing for rapid response to changing bloom dynamics. The lesson learnt underscores the promise of artificial intelligence, notably deep learning, as a strong tool for precise and scalable hazardous algae detection, paving the way for more advanced coastal ecosystem monitoring and management tactics.

VII. CHALLENGES AND FUTURE DIRECTIONS

Detecting and classifying algae using machine learning faces several challenges and offers promising future directions. Challenges include the high variability in algae species characteristics, such as size, shape, and color, making it difficult to create comprehensive datasets. Another challenge that affects models' capacity to properly generalize is the lack of annotated data available for training. Accurate categorization is further complicated by the spectrum complexity of algae and imbalanced datasets, where some species are underrepresented. In aquatic situations, real-time deployment introduces another level of difficulty. Future initiatives include utilizing transfer learning to overcome data limits, incorporating multispectral imaging for improved spectral information, and investigating deep learning architectures such as CNNs and RNNs for better feature extraction. More robust models can also be produced by using explainable AI, remote sensing technologies, and data augmentation. Multidisciplinary cooperation between environmental experts and computer scientists guarantees a thorough understanding of algal ecosystems. While there are a number of obstacles to overcome, machine learning for algal detection and classification presents exciting new opportunities. Among the difficulties are the wide variations in the features of algae species, including size, shape, and color, which make the creation of extensive databases challenging.

VIII. CONCLUSION

The investigation of dangerous algal identification culminates with a demand for continuing innovation and collaboration, ranging from taxonomic complexities to cutting-edge technologies. A comprehensive picture emerges, combining data from microscopic, molecular, and distant sensing sensors with statistical and machine learning studies. Case studies offer as realistic examples, demonstrating methodology adaptation across varied ecosystems.

Persistent detection difficulties, from early warnings to adjusting to environmental shifts, lay the groundwork for future trajectories. Emerging technologies such as artificial intelligence hold great potential for overcoming current constraints.

The conclusion emphasizes the iterative nature of advances in dangerous algal detection with a call to action. Continuous collaboration and innovation are required to meet the volatile problems provided by algal blooms. As the study comes to a close, it marks a turning point in the evolving journey toward resilient, innovative, and cooperatively determined methods to protect aquatic ecosystems and human health.

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