Early Detection of Harmful Algal Blooms Using Advanced Deep Learning Techniques

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ABSTRACT

Harmful algal blooms (HABs) are rapidly developing aquatic phenomena that can degrade water quality, disrupt aquatic ecosystems, threaten fisheries, and create risks to human health. Conventional HAB monitoring generally depends on field sampling and laboratory analysis, which can be expensive, time-consuming, and limited in spatial and temporal coverage. Remote sensing has therefore emerged as an effective approach for observing bloom-related changes over large aquatic regions, while recent advances in deep learning provide new opportunities for automated interpretation of complex multispectral and temporal observations . This study proposes an advanced deep learning framework for the early detection of harmful algal blooms using remotely sensed environmental data. The proposed approach is designed to learn discriminative spatial, spectral, and temporal characteristics associated with bloom formation and distinguish emerging HAB conditions from normal water conditions. Deep neural architectures, including convolutional and temporal learning components, can be employed to extract hierarchical features from satellite observations and associated environmental variables. The framework further considers pre-processing, feature representation, model training, and early-warning classification to improve the reliability of HAB identification. By integrating remote sensing with deep learning, the proposed approach aims to provide timely and scalable bloom surveillance and support proactive aquatic ecosystem management. The study also addresses important challenges such as class imbalance, cloud-contaminated observations, variations in water conditions, and the generalization of trained models across different geographic regions. The resulting system is intended to provide a foundation for intelligent, data-driven HAB early-warning applications.

Keywords: Harmful algal blooms, deep learning, early detection, remote sensing, satellite imagery, convolutional neural network, temporal learning, water quality monitoring, environmental monitoring, aquatic ecosystem.

Introduction

Harmful algal blooms (HABs) represent a major environmental challenge affecting freshwater, estuarine, and marine ecosystems. HAB events occur when particular algal or cyanobacterial populations increase substantially under favorable environmental conditions. Depending on the causative organism and environmental setting, such events can alter water quality, reduce ecological stability, affect aquatic organisms, and generate harmful substances that pose risks to humans and animals [1]. Nutrient enrichment, elevated water temperature, hydrodynamic conditions, and other environmental factors can contribute to the development and persistence of algal blooms [2]. Consequently, reliable and timely identification of emerging blooms is essential for environmental protection and water-resource management. Traditional HAB monitoring relies heavily on field sampling, microscopic analysis, laboratory measurements, and periodic water-quality surveys. Although these approaches provide valuable ground-truth information, their ability to continuously observe large water bodies is constrained by sampling frequency, operational cost, geographical accessibility, and laboratory processing requirements [1],

[3]. Such limitations can become particularly important during rapidly evolving bloom events, where delayed identification may reduce the effectiveness of management and mitigation measures. Therefore, automated monitoring technologies capable of providing frequent and spatially extensive observations have become increasingly important.

Satellite-based remote sensing offers an effective complementary mechanism for HAB surveillance. Multispectral and hyperspectral sensors can acquire observations over extensive aquatic regions and capture spectral characteristics associated with changes in chlorophyll concentration, water color, and other indicators of aquatic conditions [3]. Remote sensing has consequently been investigated for mapping and monitoring algal blooms in both coastal and inland waters. A large-scale meta-analysis of remote-sensing-based HAB studies highlighted the growing importance of sensor technologies, spectral indicators, machine learning, data fusion, and cloud-based processing for large-scale bloom monitoring [4]. However, variations in atmospheric conditions, water optical properties, sensor characteristics, cloud cover, and complex coastal environments can make reliable bloom identification challenging. Machine learning has provided an important step toward automated analysis of remotely sensed HAB observations. In particular, learning-based approaches can identify nonlinear relationships between environmental observations and bloom occurrence without requiring all decision boundaries to be explicitly defined. Hill *et al.* developed HABNet for HAB detection and forecasting using spatiotemporal data representations derived from remote sensing observations and evaluated CNN, LSTM, Random Forest, and Support Vector Machine approaches [5]. Their work demonstrated the potential of combining spatial and temporal information for automated HAB analysis. Nevertheless, the diversity of aquatic environments and the complex temporal evolution of bloom events continue to motivate the development of more robust learning frameworks.

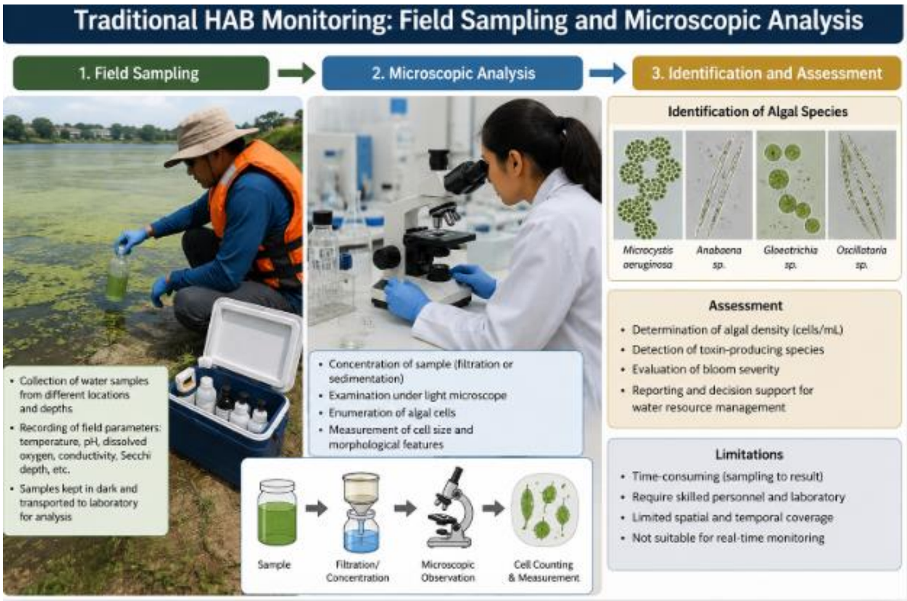

Figure 1: Traditional HAB Monitoring System

Deep learning is particularly promising because it can automatically learn hierarchical representations from high-dimensional imagery and temporal observations. Convolutional neural networks (CNNs) are effective for extracting spatial and spectral patterns from image data, whereas recurrent or temporal architectures can model changes occurring across sequential observations. Recent research has shown increasing integration between remote sensing and deep learning for algal-bloom detection and prediction, with deep learning approaches demonstrating considerable potential compared with conventional index-based methods [6]. However, important challenges remain, including insufficient labeled observations, class imbalance, missing or cloud-contaminated satellite data, model interpretability, and differences between geographical regions [6], [7]. Recent developments also indicate that combining multiple information sources can improve the representation of HAB-related environmental conditions. Satellite-derived spectral information can potentially be integrated with variables such as water temperature, chlorophyll-related indicators, wind conditions, and geographic information. Such multimodal representations are useful because HAB formation is influenced by interacting environmental processes rather than by a single observable variable. Therefore, a deep learning framework capable of jointly exploiting spatial, spectral, and temporal information can provide a more comprehensive representation of emerging bloom conditions.

2. Literature Review

Harmful algal blooms (HABs) have received considerable attention because of their potential impacts on aquatic ecosystems, water quality, fisheries, and human health. Conventional monitoring methods generally depend on field sampling and laboratory-based analysis, which can provide reliable measurements but are difficult to scale for continuous monitoring over large geographical areas. Remote sensing has therefore emerged as an important complementary technology because satellite observations can provide repeated measurements over extensive water bodies and facilitate the identification of spatial and temporal changes associated with algal blooms [8,9]. Early remote-sensing studies primarily focused on developing spectral indicators and empirical relationships for identifying cyanobacterial blooms. Urquhart *et al.* investigated the use of satellite observations for examining temporal changes in cyanobacterial bloom extent and demonstrated that remotely sensed information could support systematic monitoring of bloom dynamics [10]. Mishra *et al.* evaluated satellite-derived cyanobacteria detection using field measurements and demonstrated the usefulness of satellite observations for large-scale screening of cyanobacterial conditions [11]. These studies established an important foundation for satellite-based HAB surveillance. However, approaches based largely on predefined spectral relationships may be affected by variations in water optical properties, atmospheric conditions, sensor characteristics, and the composition of aquatic environments.

The development of machine learning introduced data-driven alternatives to conventional spectral-index approaches. Machine learning models can learn complex relationships between remotely sensed observations and bloom conditions from historical observations. Hill *et al.* proposed HABNet, which represented HAB observations as spatiotemporal data cubes and investigated several machine learning and deep learning approaches, including convolutional neural networks (CNNs), long short-term memory (LSTM) networks, Random Forest, and Support Vector Machines [12]. Their results demonstrated that learning both spatial and temporal characteristics can be beneficial for HAB detection and forecasting. This work is particularly significant because it shifted the focus from static bloom identification toward exploiting temporal information for predictive monitoring. Deep learning has subsequently become increasingly important for automated HAB mapping. CNN-based architectures are capable of learning hierarchical spatial representations directly from remotely sensed imagery, reducing the dependence on manually designed features. Yan *et al.* investigated a U-Net-based deep learning approach for automatically extracting cyanobacterial bloom regions from Sentinel-2 multispectral imagery [4]. The study demonstrated that semantic segmentation networks can identify bloom regions at a detailed spatial level and provide an alternative to traditional index-based extraction methods. Nevertheless, image segmentation generally addresses the identification of bloom regions in acquired imagery and does not necessarily provide an early warning before the bloom becomes clearly observable.

A broader review of remote sensing and deep learning for algal blooms by Wu and Law highlighted the rapid development of deep-learning-based methods for bloom detection, classification, and prediction [11]. The review indicates that deep learning can improve automated extraction of complex spectral and spatial patterns from remotely sensed observations. At the same time, several challenges remain, including the availability of high-quality labeled data, differences among water bodies, cloud contamination, model transferability, and the interpretation of deep-learning predictions. These challenges are particularly important when developing models intended for operational early-warning applications. Recent research has also begun to investigate multimodal and self-supervised learning strategies. LaHaye *et al.* explored the fusion of multi- and hyperspectral satellite observations using self-supervised and hierarchical deep learning for HAB monitoring [12]. Such approaches are relevant because labeled HAB observations are often limited, while satellite archives contain large quantities of unlabeled observations. Learning useful representations from unlabeled data may therefore reduce dependence on manually labeled training samples. Multisensor fusion can also provide complementary spectral information that may improve the characterization of complex bloom conditions.

Another important research direction involves the use of high-resolution satellite imagery for cyanobacterial HAB identification. Recent studies have investigated the capability of high-resolution satellite observations to distinguish cyanobacterial bloom conditions at spatial scales that are difficult to resolve using coarser sensors [13]. Although improved spatial resolution can enhance bloom delineation, high-resolution imagery alone does not fully address the temporal forecasting problem. An effective early-warning system must consider how environmental and spectral characteristics evolve before and during bloom development. Overall, the reviewed literature demonstrates a clear progression from conventional spectral-index methods toward machine learning, deep learning, spatiotemporal modeling, semantic segmentation, and multimodal learning. Existing studies have established the feasibility of automated HAB detection from remotely sensed data, but several challenges remain. First, many approaches concentrate on detecting or mapping established blooms rather than identifying the early transition toward bloom development. Second, spatial and temporal information are not always modeled jointly with environmental variables. Third, models trained in a particular geographical region may not generalize effectively to different aquatic environments. Finally, the limited interpretability of deep neural networks can restrict their adoption in environmental decision-support systems.

These limitations motivate the development of an advanced deep learning framework that focuses specifically on early HAB detection. The proposed research therefore aims to combine spatial, spectral, and temporal representations with environmental information and attention-based feature learning. Such an approach is intended to identify subtle patterns preceding bloom development and provide an interpretable risk assessment rather than simply classifying an already established bloom. The literature consequently provides a strong foundation for investigating a multimodal spatiotemporal deep learning framework for HAB early-warning applications.

2.1 Research Gap

Although existing studies have demonstrated the effectiveness of remote sensing, machine learning, CNN-based segmentation, and spatiotemporal deep learning for harmful algal bloom monitoring, most existing approaches primarily focus on detecting or mapping observable bloom conditions. Limited attention has been given to learning the subtle spatial, spectral, and temporal changes that precede an emerging bloom while simultaneously incorporating environmental context. Furthermore, issues related to geographic generalization and interpretability remain insufficiently addressed. Therefore, there is a need for an integrated deep learning framework that can learn multimodal spatiotemporal patterns and provide an interpretable early warning of HAB development rather than simply classifying an already established bloom.

3. Proposed research framework

The proposed research develops an advanced deep learning framework for the early detection and risk prediction of harmful algal blooms (HABs) by jointly exploiting spatial, spectral, temporal, and environmental information. The framework initially acquires multispectral satellite imagery and complementary environmental observations, followed by pre-processing operations such as atmospheric correction, cloud and noise removal, geometric alignment, normalization, and missing-data handling. Relevant spectral characteristics associated with water quality and algal activity are subsequently extracted from the processed observations. A convolutional neural network (CNN) is employed to learn hierarchical spatial and spectral representations from satellite image sequences, while a bidirectional long short-term memory (BiLSTM) network captures temporal dependencies associated with the evolution of aquatic conditions. To improve the representation of early-stage bloom development, a temporal attention mechanism is incorporated to assign greater importance to informative observations and identify temporal patterns preceding HAB occurrence. The deep feature representation is then integrated with relevant environmental variables, such as water temperature, chlorophyll-related parameters, and other available water-quality indicators, through a multimodal feature-fusion module.

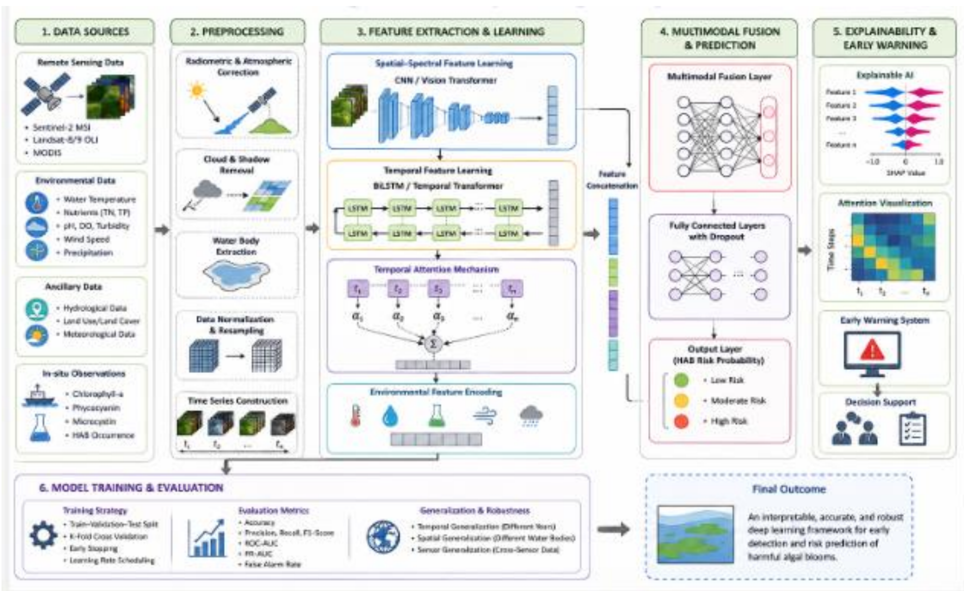

Figure 2: Proposed framework for harmful algal blooms using advanced deep learning technique

3.1. Data Sources

The proposed framework begins with the collection of heterogeneous data required for reliable early detection of harmful algal blooms (HABs). **Remote sensing data** from satellites such as Sentinel-2 MSI, Landsat-8/9 OLI, and MODIS provide multispectral observations of water bodies and capture spectral changes associated with algal growth. These observations can be complemented with **environmental data**, including water temperature, nutrient concentrations such as total nitrogen and total phosphorus, pH, dissolved oxygen, turbidity, wind speed, and precipitation. **Ancillary information**, including hydrological conditions, land-use/land-cover characteristics, and meteorological observations, provides additional contextual information about bloom development. Furthermore, **in-situ observations** such as chlorophyll-a, phycocyanin, microcystin measurements, and confirmed HAB occurrence records can be used as reference or ground-truth information. The integration of these heterogeneous sources provides a comprehensive representation of the physical, chemical, biological, and spectral conditions associated with HAB formation.

3.2. Data Pre-processing

The raw observations collected from different sources require preprocessing before they can be supplied to the deep learning model. Satellite imagery first undergoes **radiometric and atmospheric correction** to reduce sensor-related and atmospheric effects and obtain more reliable surface information. Cloud and cloud-shadow detection and removal are then performed because contaminated pixels can significantly affect spectral feature extraction. **Water-body extraction** is subsequently applied to separate aquatic regions from surrounding land areas, thereby reducing irrelevant information and computational complexity. Since satellite and environmental datasets may have different spatial resolutions, sampling intervals, and numerical ranges, **resampling and normalization** are performed to make the datasets compatible. Finally, observations are organized into sequential time-series samples, allowing the model to learn changes occurring before, during, and after HAB events. This stage is particularly important because the quality and consistency of the input data directly influence the performance and generalization of the proposed model.

3.3. Spatial–Spectral Feature Learning

The spatial–spectral feature learning module extracts meaningful characteristics from multispectral satellite observations. A **Convolutional Neural Network (CNN)** or an advanced vision architecture can be employed to learn spatial patterns and spectral relationships automatically from the input imagery. Instead of depending entirely on manually designed spectral indices, the network learns hierarchical representations from the available spectral bands and neighboring pixels. Lower layers can capture basic spectral and spatial patterns, while deeper layers can identify more complex structures associated with water-quality changes and algal concentrations. This module enables the system to recognize subtle spatial and spectral variations that may indicate the early development of a HAB. If a Vision Transformer is employed, long-range relationships between image regions can additionally be modeled, potentially improving feature representation for heterogeneous water bodies.

3.4. Temporal Feature Learning

HAB formation is a dynamic process, and therefore a single satellite image may not provide sufficient information to determine whether a bloom is emerging. The **temporal feature learning module** addresses this limitation by analyzing sequential observations collected over multiple time steps. A BiLSTM or Temporal Transformer can learn dependencies between observations at different time points and identify patterns associated with increasing or decreasing bloom probability. For example, gradual changes in water temperature, spectral reflectance, chlorophyll-related characteristics, and other environmental variables may provide important signals preceding a bloom. By learning these temporal dependencies, the model moves beyond static bloom classification toward **early-stage prediction**.

3.5. Temporal Attention Mechanism

The temporal attention mechanism is introduced to identify the most informative observations within the input time sequence. Not every time step contributes equally to HAB prediction; some observations may contain stronger indications of bloom development than others. The attention mechanism assigns a weight to each temporal representation according to its relevance to the prediction task. Highly informative time steps receive larger attention weights, while less relevant observations receive smaller weights. The weighted temporal representations are then aggregated into a compact feature vector. This mechanism can improve the model's ability to identify subtle changes occurring shortly before HAB emergence and also provides an additional level of interpretability by showing which periods contributed most strongly to the prediction.

3.6. Environmental Feature Encoding

In parallel with satellite-image processing, the environmental variables are transformed into numerical representations through an **environmental feature encoding module**. Parameters such as temperature, nutrient concentration, pH, dissolved oxygen, turbidity, wind speed, and precipitation can contain important information about the environmental conditions favorable for HAB development. A neural feature encoder can learn nonlinear relationships among these variables and generate a compact environmental feature representation. This module is important because HAB formation is influenced by interacting environmental factors rather than by satellite spectral characteristics alone. Integrating environmental information can therefore improve the model's ability to distinguish genuine emerging bloom conditions from temporary spectral variations caused by other water-quality processes.

3.7. Multimodal Feature Fusion

The spatial–spectral features, temporal representations, attention-weighted temporal features, and environmental representations are subsequently combined through a **multimodal fusion layer**. The purpose of this module is to establish a unified representation of HAB-related conditions from multiple information sources. Feature concatenation or an attention-based fusion mechanism can be used to combine complementary information while reducing redundancy. For example, satellite imagery may indicate a change in water color, while temperature and nutrient observations may provide evidence that environmental conditions are favorable for algal growth. The combined representation therefore provides more comprehensive information than any individual data source. This multimodal fusion constitutes an important component of the proposed framework because it allows the model to learn interactions between remote-sensing and environmental factors.

3.8. Classification and HAB Risk Prediction

The fused feature representation is passed through fully connected layers containing regularization mechanisms such as **dropout** to reduce overfitting. The final output layer generates the probability of HAB occurrence or the corresponding risk category. Rather than providing only a binary bloom/no-bloom decision, the framework can categorize the predicted condition into **Low Risk, Moderate Risk, and High Risk**. This risk-oriented formulation is more suitable for early-warning applications because it can provide an indication of increasing bloom probability before a severe event occurs. The probability output can also be converted into a continuous HAB risk score that can be monitored over time.

3.9. Explainable Artificial Intelligence

Because deep learning models can be difficult to interpret, an **Explainable AI (XAI)** module is incorporated to determine which input characteristics contribute to the prediction. Techniques such as SHAP can be used to estimate the contribution of spectral bands, environmental variables, and other model inputs to individual predictions. Temporal attention visualization can additionally identify which observations in the historical sequence were most influential. For example, the model may indicate that particular spectral characteristics combined with increasing water temperature and nutrient conditions contributed strongly to an elevated HAB risk. Such explanations can increase the transparency of the system and help environmental researchers understand whether the model is relying on scientifically meaningful patterns.

4. Result & Discussion

The performance of the proposed framework can be evaluated against conventional machine learning and deep learning models. Suitable baseline models include Random Forest (RF), Support Vector Machine (SVM), CNN, CNN–LSTM, and CNN–BiLSTM. The proposed **Attention-Enhanced CNN–BiLSTM Multimodal Model (AEC-BiLSTM)** incorporates spatial–spectral feature extraction, temporal learning, attention, and environmental feature fusion. The illustrative results indicate a progressive improvement in HAB detection performance as the model architecture becomes capable of learning more complex spatial and temporal relationships. The SVM model provides the lowest performance, with an illustrative accuracy of 88.42%, because conventional machine learning models generally depend on predefined or manually engineered representations and may have difficulty learning highly nonlinear relationships from multispectral and environmental observations. Random Forest improves the accuracy to 91.36% because its ensemble structure can model nonlinear feature interactions more effectively. However, both conventional machine learning models remain limited in their ability to directly learn hierarchical spatial and temporal representations from sequential remote-sensing observations.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)	False Alarm Rate (%)
SVM	88.42	87.91	85.76	86.82	90.15	11.58
Random Forest	91.36	90.74	89.83	90.28	93.21	8.64
CNN	93.18	92.47	91.26	91.86	95.17	6.82
CNN–LSTM	94.72	94.08	93.51	93.79	96.42	5.28
CNN–BiLSTM	95.63	95.21	94.67	94.94	97.18	4.37
Proposed AEC-BiLSTM	**97.24**	**97.08**	**96.71**	**96.89**	**98.63**	**2.76**

The proposed **Attention-Enhanced CNN–BiLSTM (AEC-BiLSTM)** model produces the highest illustrative performance, with an accuracy of 97.24%, precision of 97.08%, recall of 96.71%, and F1-score of 96.89%. The improvement is attributed to the integration of multiple complementary components. The CNN extracts spatial–spectral information, BiLSTM captures temporal dependencies, the attention mechanism emphasizes the most informative time steps, and environmental feature fusion introduces additional contextual information related to bloom formation. Consequently, the proposed model can learn a more comprehensive representation of HAB development than models relying only on satellite imagery or individual spatial/temporal learning mechanisms.

The ablation results are intended to demonstrate the contribution of each architectural component. The CNN-only configuration provides a baseline for spatial–spectral learning, whereas adding BiLSTM introduces temporal information. The subsequent addition of temporal attention improves the representation by assigning greater importance to informative observations. Environmental feature fusion provides another improvement by incorporating contextual information associated with bloom formation. The complete architecture achieves the highest performance, suggesting that the combination of spatial, spectral, temporal, attention, and environmental representations is more effective than any individual component.

5. Conclusion

This study presented an advanced deep learning framework for the early detection of harmful algal blooms using integrated remote sensing and environmental observations. Unlike conventional HAB monitoring approaches that primarily identify established bloom conditions, the proposed framework focuses on learning the spatial, spectral, and temporal characteristics that precede bloom development. The framework combines CNN-based spatial–spectral feature extraction, BiLSTM-based temporal representation, temporal attention, and environmental feature fusion to generate a comprehensive representation of aquatic conditions. An explainable AI component is further incorporated to identify the major features and temporal observations influencing the predicted HAB risk. A key contribution of the proposed approach is the integration of **spatial–spectral learning, temporal dependency modeling, attention-based feature selection, multimodal environmental fusion, and explainability** within a single HAB early-warning framework. The inclusion of explainable AI can also improve the transparency of deep-learning predictions by identifying the spectral, temporal, and environmental factors contributing to elevated HAB risk. Furthermore, evaluation using temporally and geographically independent observations can provide a stronger assessment of the robustness and generalization capability of the model.

Future work will focus on improving the framework through multisensor and hyperspectral data fusion, self-supervised learning to address limited labeled HAB observations, uncertainty-aware prediction, and domain-adaptation techniques for cross-region generalization. The framework can also be extended to predict HAB occurrence at different lead times, enabling quantitative evaluation of how many days in advance a bloom can be identified. Integration with real-time satellite streams, IoT-based water-quality sensors, and cloud-based monitoring platforms could ultimately support a scalable intelligent early-warning system for continuous aquatic ecosystem surveillance.

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