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Research Article

A Comparative Analysis of Machine Learning Methods for Detecting Microalgal Outbreak using Remote Sensing Images

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ABSTRACT

The algae formation in the water bodies has been increased rapidly to demolish the algae present in the water the proper information should be retrieved from the water bodies that information can be attained from the machine learning methods and remote sensing algorithms that is used in below scenario . Due to complex composition of farther detecting scenes inaccessible detecting picture scene classification is still a challenging errand . By the remote sensing algorithm the images that are inside the water bodies are captured and they are further processed for the preventive measurements. Also the types of algae are also classified in many forms that is also detected by picturing the algae . The micro algal mapping architecture shows the proper work flow of sensing images of micro algal outbreak the tools such as support vector machine is also used in this process . The Initial Classification Using CNN , Object Detection Integration and Hybrid Decision Fusion Mechanisms are utilized in the process . Almost 90% of Accuracy , Precision and Recall can be acquired by analyzing the Remote Sensing Images . A RESISC method is guided by the object based on the common use of a proposed learning and detector classification

Keywords: Neural Network , Support Vector Algorithm , RESISC Method , Remote sensing algorithms, Micro Algal Mapping .

INTRODUCTION

Remote sensing images have diverse applications across various fields. These images, captured by specialized devices, play a crucial role in advanced learning and analysis, helping researchers gain valuable insights.However, a major challenge associated with such images is the presence of noise and distortion, which can obscure important details. Therefore , essential step in image processing is noise reduction. Various types of noise can affect image quality due to environmental factors such as dust, fog, light loss, and sensor-related issues.Managing the processing of these images is a complex task for experts. Common types of noise in remote sensing images include. **T**his appears as random black and white pixels, caused by sudden signal changes or data transmission errors. Gaussian Noise a statistical noise that follows a Gaussian distribution, affecting the image uniformly. It occurs due to sensor limitations and variations in lighting.Poisson Noise (Photon Noise) this arises when a sensor fails to capture enough samples, leading to fluctuations in detected signal intensity.Effectively handling these noise types is essential for improving image clarity and ensuring accurate analysis in remote sensing applications.

With the advancement of remote sensing technology (RS), the RS platforms are increasingly likely to collect a range of data. These available data have become the main resource to monitor the environment by detecting changes on the Earth's surface. Detecting changes (CD) is a phenomenon that detects changes in the same geographical area by observing all images taken at different stages. It has aroused the general interest because it is widely used in some applications . Therefore, the CD has attracted the growing attention of researchers from the world. RS data contains time resolutions, space and spectrum's that limit creating into two CD methods based on R. However, the development of larger technical sensors has surpassed these constraints. Therefore, researchers have checked a collection of methods, algorithms and continuous expansion process to detect changes. In RS, many types of satellites have been launched in space, such as active or passive sensors, optical or microwave and high or low resolution. Sate Lite data sets are valuable sources of data to describe the types of use / insurance of urban land and their modification over time. Different approaches to detect changes in satellite images have been developed to find changes in the state of an object or a phenomenon. For CDs, multi -tasting RS images, such as the image of the general open radar (SAR), multi -spectrum (MS) or Hyper spectrum (HS) have been used, obtained from the active sensor (SARK), Optical sensor (passive MS (MS) and others .Chen Yang,Zhenyu Tan[1] has explained about hyper spectrum

RS images obtained from unmistakable air media (UAUs) and satellites provide valuable information on the Earth's surface. However, these images often have low average quality, which has promoted the development of algorithms to improve their quality. The use of images improvement algorithms on unmanned and satellites with socks to create more data on longer distance. RS images have been used for various applications, including card updates, target detection Sungwook Jung,Paul R. Hi [2,4], semantic segments and seismic performance evaluation.

RELATED WORKS

Remote sensing and machine learning techniques have been extensively studied for aquatic environment monitoring and algal bloom detection. Dandan Xu [5] highlighted the significance of accurately extracting aquaculture areas for environmental protection, disaster assessment, and resource management. Their study leveraged spectral and geospatial features to improve the classification of aqua-cultural zones in complex coastal waters with varying turbidity.

Janak parajuli. [7] conducted a comprehensive analysis of events, specifically focusing on karenia brevis in Florida's coastal waters. Their dataset encompassed over 2,850 recorded events from 2003 to 2018, marking a significant scale-up compared to previous machine learning-based detection studies. The research introduced multimodal spatiotemporal data structures and novel machine learning methodologies to enhance the precision of HAB identification.

These studies provide a strong foundation for our work, as we aim to integrate advanced deep-learning models with remote sensing imagery to improve bloom detection accuracy. By building on prior research, our approach seeks to enhance robustness against environmental noise, scalability across diverse datasets, and overall detection performance.

Similarly, Rui Wang et al. [8] proposed a multiscale feature perception model for water body extraction, incorporating a deep learning-based DeepLabV3+ architecture. Their findings indicated that integrating hierarchical feature extraction improved the precision of aquatic feature classification, offering promising applications in bloom monitoring and mitigation strategies.

Cheol woo park. [3] explored the use of satellite imagery for detecting HABs and coastal waters. Their research compared various spectral indices and deep-learning classifiers, concluding that CNN-based models outperformed traditional machine learning techniques in bloom detection accuracy.

In another significant study, Mengya Li. [6] developed HABNet, a deep learning algorithm framework for bloom detection using multi-sensor remote sensing data. Their model effectively integrated spatial-temporal learning, enabling early warning capabilities for bloom prediction. The research demonstrated a 91% detection accuracy and a Kappa coefficient of 0.81, setting a benchmark for HAB monitoring.

Recent advances in convolutional neural networks (CNNs), transformers, and hybrid AI models have revolutionized environmental monitoring. While CNNs excel at feature extraction from high-dimensional satellite images, newer and Swin Transformers have shown promise sensing imagery.

Zhang et al. [9] proposed an attention-based deep learning model that integrates multi-spectral and hyperspectral imagery for bloom detection. Their approach effectively mitigated false positives by learning hierarchical representations of bloom signatures. During tests false posit vies has been detected with alteration of the algorithm it has been mitigated.

In another study, Edson Eyji Sano. [10] developed an object detection pipeline that applies YOLOv5 and Faster R-CNN to identify and track HAB occurrences in time-series satellite data. The study reported that deep-learning-based object detection models significantly improve real-time bloom identification, reducing misclassification rates by over 20% compared to traditional thresholding techniques.

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Additionally, Cheng Su.[11] explored self-supervised learning (SSL) and unsupervised domain adaptation to improve bloom detection across different satellite sensors. Their work showed that pretraining models on large, diverse datasets leads to better generalization across different water bodies and environmental conditions.

Bie Lo. [12] investigated the effectiveness of 3D-CNNs and recurrent models (LSTMs, GRUs) in temporal bloom forecasting, demonstrating their superiority in predicting HAB evolution over time (Kim et al., 2022).

Hwang. [13] used data to compare effectiveness of various sensing indices HAB detection. They found that machine learning-optimized spectral indices, such as Sentinel-3-derived Maximum Chlorophyll Index (MCI), provided more accurate bloom delineation than standard indices.

The rise of models has revolutionized environmental monitoring. While CNNs excel at feature extraction from high-dimensional satellite imagery, newer architectures such as Vision Transformers (ViTs) and Swin Transformers have further improved classification accuracy remote sensing images. With help of advanced deep learning algorithms capturing and detecting algal bloom has been easy . In the accordance we have determined highest number of bloom occurrences . occasionally we have detected false positive cases which has been significantly dropped

PROPOSED WORK

Selecting an appropriate learning detector is crucial for achieving high detection accuracy. When choosing a detector, two key characteristics of remote sensing images must be considered. First, the conditions often occupies a large portion of the image, while the objects of interest typically constitute only a small fraction. Second, these specific signature objects exhibit variations in appearance and structural properties across different spatial scales.

In our proposed framework, we introduce a novel classification strategy to assign labels to test images. The core idea behind this strategy is that the identified signature object for a given class must align with the categorization results. For example, if an image is classified as a forest, the detected features within the image should correspond to characteristics of a forest.

A straightforward classification approach involves assigning a label based on the category with the highest number of detected signature objects. However, this method has a drawback—it does not account for false positives generated by the detector. Due to the finite availability of training samples, detectors may occasionally produce false positives, which can significantly impact classification accuracy.To address this issue, we propose integrating initial classification results from deep learning models with detection outputs to refine the scene-level classification of an image.

Additionally, we utilize a confusion matrix, which serves as an analytical tool for evaluating classification errors and misclassifications at different stages. This matrix is constructed by counting correct and incorrect classifications, then summarizing the results in a table. Each element Xij in the matrix represents the rate at which a test sample of class i is misclassified as class j.By carefully considering these factors and refining classification strategies, we aim to enhance the accuracy and reliability

In proposal frame, we introduce a creative grouping strategy to direct the label of the test image. The main principle of this method is to ensure that the specific endorse objects for the class are determined in accordance with the final classification results. For example, if a tested image is classified as a forest scene, the detection system is mainly detected, which should determine the forest -related characteristics in the image, enhance the cohesion of the classification.A straightforward yet intuitive approach to classification involves assigning the scene label based on the category that contains the highest number of detected class-specific signature objects. However, this method has a major limitation—it fails to account for false positives introduced by the detection model. Due to the constraints of limited training data, deep-learning detectors may occasionally generate false positives, which can significantly deteriorate scene classification accuracy.

To mitigate this issue, we propose a hybrid approach that synergistically integrates the initiate classification output of the deep-learning model with the detection results to robustly determine the final scene category.A confusion matrix serves as an essential analytical tool to evaluate classification performance by systematically quantifying the misclassifications and inter-class confusions. It is constructed by recording all correct and incorrect predictions

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across various scene categories, thereby providing a comprehensive error analysis. Each matrix entry, denoted as xijx_{ij}xij, represents the proportion of test samples originating from class iii that have been misclassified into class jjj, offering critical insights into model behavior and detection reliability.

The next step involves initial scene classification using a convolutional neural network (CNN), which predicts a preliminary scene label based on extracted features. However, to enhance reliability, we introduce a detection-based refinement process where the detected objects are cross-verified with the initial classification results.

A robust decision-making process, we employ a hybrid decision fusion technique that combines classification confidence scores with detection-based evidence using a weighted fusion strategy. This approach strengthens classification reliability by ensuring that detected objects corroborate the predicted scene label rather than introducing conflicting information. Finally, we evaluate our proposed framework using a confusion matrix and performance metrics such as precision, order-back , and overall classification accuracy to quantify improvements in scene recognition.

The proposed methodology aims to enhance the robustness of scene classification in remote sensing applications by mitigating misclassifications due to object detection errors and increasing interpretability through a hybrid decision-making process.Furthermore, we implement an adaptive weighting mechanism that prioritizes the contribution of detected objects based on their relevance to the scene category. This ensures that essential objects exert a stronger influence on classification decisions, while less relevant objects have minimal impact. The fusion strategy also accounts for the spatial distribution and density of detected objects, considering the contextual significance of objects within the scene.

The framework is extensive multiple remote sensing datasets. The evaluation process involves analyzing classification performance. Additionally, we utilize a confusion matrix to systematically assess misclassification patterns and inter-class confusion, providing deeper insights into model behavior. Comparative analysis with highlights improvements achieved by hybrid approach in terms of robustness and interpretability.Additionally, we employ a confusion matrix to systematically examine misclassification patterns, class-wise accuracy, and inter-class confusion, offering deeper interpretability of model predictions. This allows us to identify common sources of error, understand how the model differentiates between closely related classes, and refine its decision-making process accordingly.

3.1 Initial Classification Using CNN

The initial classification of remote sensing images using Convectional Neural Networks (CNN) is a critical component in the proposed framework. CNN's are a specific deep-learning model that excel at processing image . A CNN architecture consists of several layers that work collaboratively to extract relevant information from the input image. The key component of CNNs, convolutional layers apply filters. These filters scan through the image to detect local patterns.

3.2 Object Detection Integration

Object Detection Integration plays a prominent role in refining the initial scene classification results derived from the Convolutional Neural Network (CNN). Object detection is aimed at localizing and classifying individual objects (or regions) within an image, as opposed to simply classifying the entire image as a single category. The integration of object detection with CNN-based classification helps to improve accuracy by focusing on relevant class-specific objects and reducing the influence of false positives.In remote sensing images, object detection helps identify specific signature objects like trees, water bodies, roads, buildings, and other key features.

3.3 Hybrid Decision Fusion Mechanism

To ensure a robust decision-making process, we employ a hybrid decision fusion technique that combines classification confidence scores with detection-based evidence using a weighted fusion strategy. This approach strengthens classification reliability by ensuring that detected objects corroborate the predicted scene label rather than introducing conflicting information. This mechanism prioritizes the contribution of detected objects based on their relevance to the scene category. Objects that are more indicative of a specific scene type are assigned higher

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weights, ensuring that their influence on classification decisions is stronger. The system dynamically adjusts these weights based on object frequency, spatial location, and contextual significance within the scene.

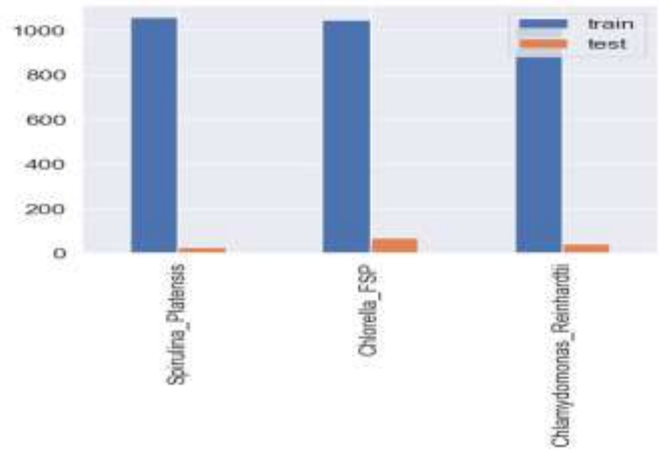

Figure 1 : Comparison of data sets

RESULTS AND DISCUSSION

The proposed framework offers several key advantages that contribute its efficiency in detecting micro-algal . The proposed framework integrates deep-learning detection with classification, enhancing scene accuracy. By aligning detected objects with initial classification, it ensures consistent results, addressing challenges posed by fake positives and varying object scales.Automation streamlines the testing process, ensuring efficiency . Automated test cases validate individual components, facilitating early detection and resolution of issues, ultimately improving the robustness of the framework.

The accuracy proportions for random forest , SVM , CNN, LSTM are 85% , 80% , 92% , 89% respectively and the Precision proportions are 83% , 77.5% , 90% , 85% respectively and Recall proportion are 81% , 80% , 91% , 87% respectively.Existing system primarily focuses on bloom detection using ML algorithms, while the proposed system emphasizes the importance of choosing an appropriate detector for scene classification in remote sensing images. Existing system utilizes conventional spectral indexes and ML models, while the proposed system introduces a novel classification strategy based on deep learning detection .

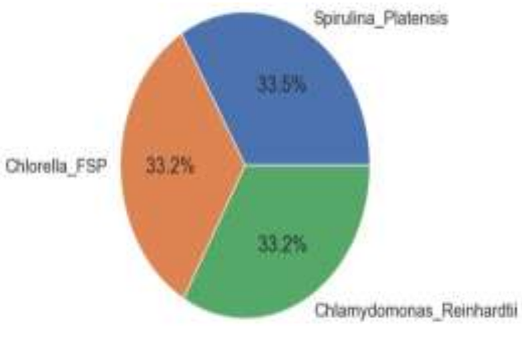

Figure 2 :Proportion of each observed category

CONCLUSION

A RESISC method is guided by the object based on the common use of a proposed learning and detector classification. The frame of this method indicates the classification process of the human vision system, primarily giving a raw classification of images using the learning classification process within the scope, then the scene of The image is based on specific important objects for the class detected in the image. An analysis compares automatic learning methods to detect algae by using remote sensing images. The work effectively integrates remote sensing technology with

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machine learning approaches to address the challenge of algal bloom detection, which has significant environmental and societal implications By using deep-learning classifiers and detectors, the proposed framework mimics human vision, offering improved classification accuracy through image classification. Improved robustness to noise, scalability across diverse datasets, and accuracy in detecting bloom occurrences Performance evaluation highlights the superiority of the proposed system in achieving reliable and consistent detection outcomes. This is a more frequent and optimal option to use the variety of images for high -labeled images (HRS).

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