Universal Robust Domain Adaptation for Remote Sensing Image Classification using Deep Optimized Transfer Learning

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Abstract

The detection of algal blooms in lakes and reservoirs via remote sensing presents a significant environmental challenge, impacting aquatic ecosystems and human health. While conventional algorithms relying on remote sensing reflectance have shown effectiveness in certain contexts, achieving high accuracy across multiple lakes remains a challenge, particularly with single- threshold-based approaches. This study investigates the performance of various machine learning (ML) algorithms for pinpointing algal bloom locations using Sentinel-2 images in Chinese eutrophic inland lakes. Through comprehensive testing of four ML models - random forest (RF), extreme gradient boosting, artificial neural network, and support vector machine - in lakes Taihu, Chaohu, and Dianchi, alongside index-based methods such as the floating algae index, this research provides insights into their accuracy, stability, and robustness. Results indicate that the RF model exhibits superior performance compared to other ML models, maintaining an overall accuracy above 0.90 across various lakes. Notably, even when trained on data from a single lake, the RF model achieves a commendable accuracy of 0.88 for other lakes. In summary, this comparative analysis underscores the promising potential of ML techniques in enhancing the detection of algal blooms in diverse remote sensing scenarios.

Key Words: *Algal blooms, remote sensing, , random forest, extreme gradient boosting, artificial neural network, robustness, comparative analysis.*

I.Introduction

Remote sensing imagery serves as a critical tool across diverse fields, offering valuable insights into various phenomena. However, these images often suffer from noise and blur, necessitating rigorous preprocessing, particularly for tasks like image denoising. Noise in remote sensing images arises from multiple sources, including environmental conditions, sensor imperfections, and data transfer errors, manifesting as salt & pepper, Gaussian, or Poisson noise.With advancements in remote sensing (RS) technology, RS platforms have become increasingly adept at collecting vast datasets, crucial for environmental monitoring and change detection (CD) on the Earth's surface. CD, the process of detecting alterations in a geographical area over time, finds wide application in fire detection, disaster monitoring, and urban change analysis. However, the limited temporal, spatial, and spectral resolutions of RS data have historically constrained CD methodologies.To address these limitations, researchers have explored diverse RS sensors, including optical and microwave sensors, as well as active and passive satellites. Additionally, the emergence of unmanned aerial vehicles (UAVs) has provided valuable high- resolution RS data, albeit with challenges such as image quality. Consequently, algorithms for image enhancement have been developed to improve data quality.One significant challenge in RS imagery is stripe noise, prominently observed in datasets like MODIS, affecting various applications. The stripe noise, whether periodic or non-periodic, arises from mechanical movements during sensing or spectral and temperature factors. Effectively removing such noise remains a key research focus.Algal blooms, a major environmental concern, have spurred extensive research leveraging remote sensing data for timely and accurate monitoring. Satellite imagery, particularly from sensors like MODIS and Sentinel-2, enables the detection of algal blooms on a large scale. While MODIS provides wide coverage, sensors like Sentinel-2 offer higher spatial resolutions, enhancing detection capabilities Spectral differences between visible and infrared ranges enable the discrimination of algal blooms from normal water bodies. Various spectral indices, such as NDVI and EVI, have been employed for algal bloom detection, alongside machine learning (ML) algorithms. ML techniques, including SVM, XGBoost, and CNN, show promise in accurately identifying and classifying algal blooms based on remote sensing imagery.However, the performance and applicability of these algorithms across different lakes remain unclear. This study aims to comprehensively evaluate the performance of commonly used ML algorithms, including XGBoost, ANN, SVM, and RF, for algal bloom detection in multiple lakes using Sentinel-2 imagery. Additionally, traditional index-based methods are compared to provide insights into model accuracy and robustness. The study also investigates the transferability of ML models across different lake environments, offering valuable insights for algal bloom detection efforts.

II. LITERATURE REVIEW

Monitoring water bodies using remote sensing data is crucial for assessing the current state of available water resources, promoting environmental conservation, sustainable development, and various other applications. While Sentinel-2 images are highly desirable for this task, conventional index- based and deep learning-based methods for water extraction still face significant challenges in effectively handling extensive and diverse areas. This is because different types of water bodies with varying spatial and spectral characteristics are naturally present, posing limitations to existing methods[1].

Surface water serves as a vital resource in urban settings. Tracking the spatial and temporal patterns of urban surface water using remote sensing imagery is essential for effective urban planning and management. However, the accuracy of methods relying on low to medium resolution images is hindered by the inherent limitations in spatial resolution, making it challenging to precisely identify small water bodies[2].

Algal bloom represents a significant worldwide concern for inland waters, presenting a substantial risk to aquatic ecosystems. Prompt and precise detection of algal blooms is essential for effectively managing, controlling, and predicting their occurrence. Optical satellite imagery, known for its frequent revisits, is extensively employed for monitoring algal blooms in both marine environments and expansive inland water bodies[3].

Deep learning has gained prominence as a prevalent technique for extracting water bodies from remote sensing imagery. Nevertheless, these approaches often target a particular sensor and lack versatility. Hence, we introduce a novel network known as the dense-local- feature-compression (DLFC) network, designed to automatically extract water bodies from various remote sensing images[4].

This study endeavors to introduce a fresh methodology designed to differentiate the prevailing land use and land cover (LULC) classifications in Brazil by leveraging PROBA-V images. In this approach, the PROBA-V images undergo a transformation process, wherein they are converted into distinct fractions representing various elements such as vegetation, soil, and shade. This innovative method offers a comprehensive and nuanced understanding of the LULC dynamics in Brazil, allowing for more precise and insightful analyses of the country's diverse landscape features and environmental characteristics. Through the utilization of PROBA-V imagery and the derived fractions, researchers gain valuable insights into the intricate interplay between different land cover types, paving the way for informed decision-making in land management, conservation efforts, and sustainable development initiatives across Brazil[5].

Precisely delineating aquaculture areas holds considerable importance for effective aquaculture management, post-disaster assessment, and safeguarding aquatic environments. Despite this, limited focus has been directed towards extracting aquaculture areas in coastal waters characterized by high turbidity levels. In this investigation, we explore the spectral and geospatial characteristics of aquaculture cages situated in intricate coastal waters exhibiting fluctuating turbidity levels[6].

This study has specifically concentrated on detecting Karenia brevis algae (K. brevis) harmful algal bloom (HAB) occurrences within Florida's coastal waters. The research spans from 2003 to 2018 and encompasses over 2850 events, representing a significantly larger dataset compared to prior machine learning studies on HAB detection. The development of multimodal spatiotemporaldatacube structures, along with innovative machine learning techniques, offers a distinctive framework for automatically detecting environmental events. When applied to HAB detection, this approach achieves a maximum accuracy of 91% and a Kappa coefficient of 0.81 for the Florida dataset analyzed. Furthermore, a HAB forecast system has been devised, utilizing temporal subsets of each datacube to predict the future occurrence of HABs[7].

The procedure comprises several steps, including the division of images into multiscale features, restructuring of the deep learning network model, joint prediction across multiple scales, and postprocessing optimization using a fully connected conditional random field (CRF). In line with the scale space theory in remote sensing, we implement hierarchical multiscale division processing on images. Subsequently, we enhance the architecture of the DeepLabV3+ model, which is an advanced image semantic segmentation model, and modify the feature output layer of the model to incorporate multiscale features through weighted fusion[8].

The proposed approach serves as an initial phase in the development of automated systems for the early detection, alerting, and swift response to harmful algal bloom (HAB) contamination in inland water bodies. Initially, we segment the image into uniform regions using a density-based spatial clustering algorithm (DBSCAN), followed by the extraction of water bodies from the segmented regions using wavelet leader-based texture analysis[9].

The ARROS (Autonomous Removal and Remote Observation System) is designed with a catamaran- style unmanned surface vehicle (USV) equipped with an algae removal device. Additionally, it incorporates electrical control systems and a guidance, navigation, and control (GNC) system to autonomously eradicate algal blooms. Furthermore, for enhanced operational efficiency, an unmanned aerial vehicle (UAV) is employed, and the system employs an image-based detection algorithm, referred to as a local binary, to identify algal blooms[10].

III METHODOLOGY

Our methodology is designed to address the challenges posed by limited continuous satellite temporal data and variations in lag time among the controlling factors influencing Harmful Algal Blooms (HABs). By leveraging remote sensing datasets, Geographic Information System (GIS)technologies, and machine learning data-driven modeling, we aim to provide predictive insights into HAB occurrences up to nine days in advance, while gaining a deeper understanding of the factors governing their onset. Our approach hinges on the utilization of both dependent and independent variables to capture hidden patterns in the ecosystem dynamics. The independent variables represent factors correlated with HAB bloom growth and propagation, while the occurrences of HABs serve as the dependent or response variable.The workflow of our methodology unfolds across four key steps, each contributing to the comprehensive analysis of HAB dynamics. Firstly, we initiate the process by downloading and meticulously processing daily Moderate Resolution Imaging Spectroradiometer (MODIS) data. This step ensures a robust foundation of satellite-derived information for subsequent analyses. Subsequently, we embark on the development of statistical models, encompassing both linear and non-linear frameworks. These models are constructed based on historical records of HAB occurrences and ocean color products derived from consecutive-day MODIS data.Following model development, our methodology advances to the critical phase of model comparison. Here, we rigorously assess the performance of the constructed models, evaluating their predictive accuracy and capacity to capture the nuances of HAB dynamics. Through meticulous comparison, we identify strengths and weaknesses inherent in each model, paving the way for informed decision-making in the subsequent step. Finally, armed with insights gleaned from model evaluation, we proceed to select the optimum model and its corresponding structure. This selection process is guided by a comprehensive understanding of the intricate interplay between various factors influencing HAB occurrences, as illuminated by our data-driven approach. By adhering to this structured methodology as shown in figure 1, we aim to furnish stakeholders with actionable insights for proactive management and mitigation of HAB events.

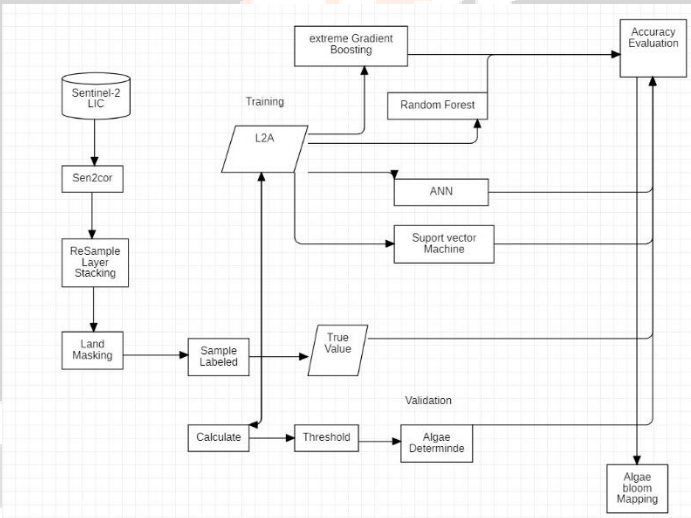

Figure 1, Data flow diagram

IV DISCUSSIONS

A.IMPACT OF ADVANCED TECHNOLOGIES IN EPILEPTIC SIGNAL CLASSIFICATION:

The integration of Industry 4.0 technologies marks a significant advancement in the realm of epilepsy detection, offering profound benefits in signal classification. While previous studies have not extensively explored the potential of AI, additive manufacturing (AM), augmented reality (AR), virtual reality (VR), robotics, and cloud-to-ground communication (CgC) in this domain, their transformative impact is evident. AI-driven algorithms present a promising solution to address the challenges posed by unstructured data, facilitating the optimization of multi-objective models for enhanced traceability and cooperation within epilepsy detection systems. Furthermore, AM streamlines critical processes such as electrode manufacturing, resulting in substantial reductions in time, labor, and resource requirements. VR technology emerges as a powerful tool for digitalization, offering simulations of data analysis and insights into production requirements across geographically disperse locations. Additionally, robotics and machine learning techniques bolster operational efficiency by facilitating accurate analysis and prediction of patterns, thereby providing invaluable insights for epilepsy detection.

B.DIFFICULTIES IN IMPLEMENTING ADVANCED TECHNOLOGIES:

Despite the myriad advantages offered by advanced technologies, their integration into epilepsy detection systems is not devoid of challenges. Stakeholders, particularly healthcare providers, may encounter obstacles related to technology adoption, especially in regions with limited access to education and resources. Upskilling initiatives and educational programs play a pivotal role in empowering stakeholders to effectively harness advanced technologies. Furthermore, concerns surrounding energy consumption, legal regulations, and data privacy pose significant hurdles to the widespread adoption of Industry 4.0 technologies in epilepsy detection. Building trust among stakeholders and ensuring robust accountability of data are essential steps in overcoming resistance to technology adoption and mitigating potential risks associated with implementation.

C.TECHNOLOGY COST SHARING MECHANISMS:

Collaborative approaches to technology ownership and cost-sharing mechanisms are indispensable for the sustainable development of epilepsy detection systems. Establishing partnerships with technology providers facilitates the implementation of cost-sharing arrangements, wherein profits are equitably distributed based on the level of technology usage and the value added by each entity. Subscription-based models and revenue-sharing agreements offer viable avenues for sharing the costs of technology ownership and operation, ensuring accessibility and sustainability in the deployment of advancedtechnologies for epilepsy detection. By fostering collaboration and equitable distribution of resources, these mechanisms drive innovation and facilitate widespread adoption, ultimately contributing to the advancement of epilepsy diagnosis and management.

V ARCHITECHTURE

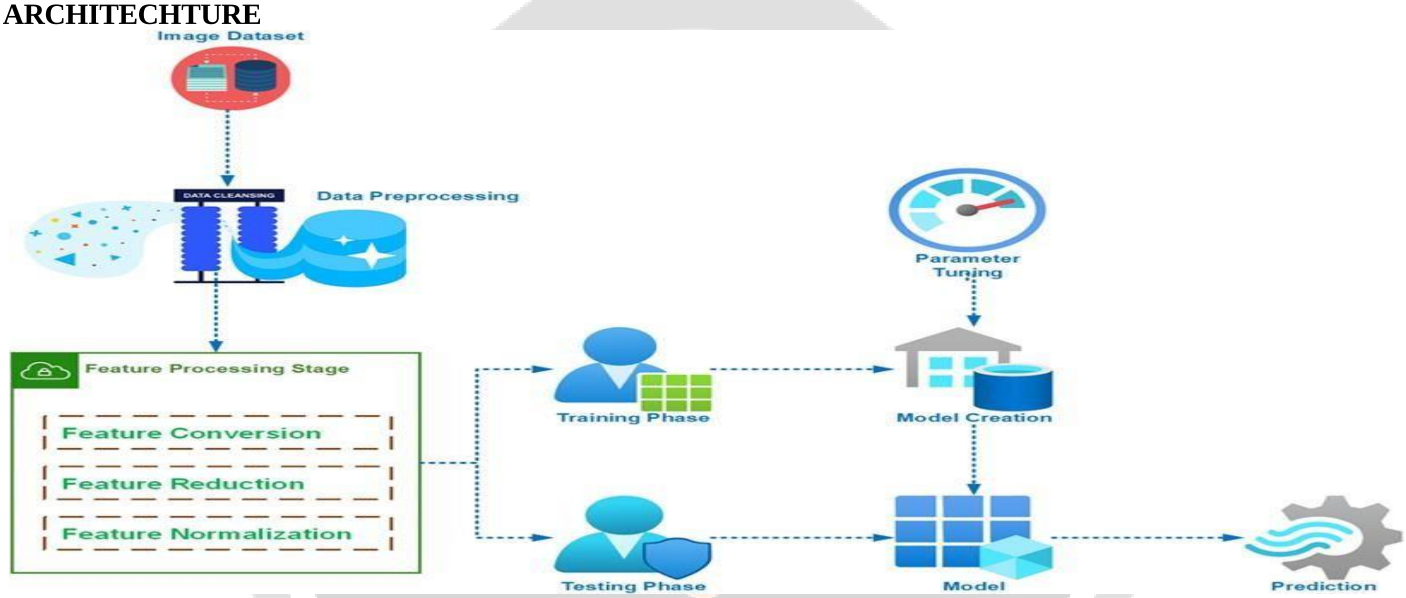

Figure 2, The general architechture diagram

As shown in Figure 2, The feature processing system depicted in the flowchart involves several key stages aimed at transforming raw data into a format suitable for training a predictive model.Initially, the system begins with the collection of data from an image dataset, which serves as the foundation for subsequent processing. This data is then subjected to a data preprocessing stage, where it undergoes cleansing and formatting to eliminate inconsistencies and prepare it for feature extraction.The core component of the system is the Feature Processing Stage, where the data is transformed into features that the model can comprehend. This stage comprises three sub- steps: Feature Extraction, Feature Reduction, and Feature Normalization. During Feature Extraction, relevant features are extracted from the data, capturing essential information for training the model. Following this, Feature Reduction is performed to decrease the number of features, thereby enhancing computational efficiency and reducing the risk of overfitting. Subsequently, Feature Normalization is applied to scale the features to a common range, ensuring uniformity and facilitating the learning process for the model.Once the features are processed, the next step involves Model Creation, where the processed features are utilized to train a predictive model. During this stage, parameters are fine-tuned to optimize the model's performance and enhance its predictive capabilities.Finally, the trained model undergoes Model Testing, where its performance is evaluated using a separate testing dataset. In this phase, the model's ability to make accurate predictions on new, unseen data is assessed, providing insights into its effectiveness and generalization capabilities.Overall, the feature processing system serves as a critical pipeline for transforming raw data into actionable insights, enabling the development of predictive models capable of making informed decisions on new data instances.

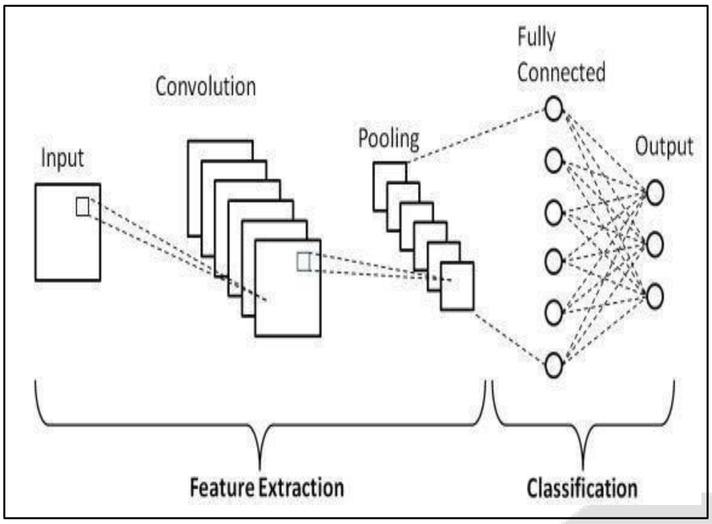

Figure 3, CNN architechture.

The figure 3, illustrates the process flow of a Convolutional Neural Network (CNN), a specialized type of artificial neural network widely used for image recognition and processing.The process begins with the Input layer, where image data is fed into the network. From there, the data undergoes Convolution, where features such as edges, lines, and shapes are extracted from the input image. This convolutional layer plays a crucial role in identifying patterns within the image data.Following Convolution, the data is passed through a Pooling layer, which serves to reduce the dimensionality of the data. Pooling helps to enhance the efficiency of the network and mitigates the risk of overfitting by condensing the extracted features.The combination of Convolution and Pooling layers effectively performs Feature Extraction, capturing relevant information from the input image.Subsequently, the processed data is fed into a Fully Connected Layer, akin to traditional neural network layers. Here, the extracted features are utilized to classify the image, determining its category or label.Finally, the network concludes with the Output layer, which produces the classification results based on the features extracted and the classification process performed in the Fully Connected Layer.In essence, the CNN systematically processes image data, extracting meaningful features and utilizing them for accurate classification, making it a powerful tool in image recognition and analysis tasks.

VI ALGORITHM

1. Data Collection:

   - Gather remote sensing images containing algal bloom data, ensuring coverage across various regions and time periods.

2. Pre-processing:

   - Normalize the intensity values of pixels in the images to a specific range (e.g., 0-1 or -1 to 1) to improve the training process and CNN model performance.

3. Apply CNN Model:

   a. Convolutional Layers:

   - Extract features from the images using convolutional filters that learn to detect specific patterns or features within the image.

   b. Pooling Layers:

   - Reduce the dimensionality of the data by downsampling the feature maps, controlling model complexity and preventing overfitting.
   - Implement pooling operations such as max pooling or average pooling.

   c. Fully Connected Layers:

   - Perform high-level reasoning on the extracted features, arranged in a stack to transform the output from previous layers using linear functions.
   - Produce the final output of the network, corresponding to algal bloom classification.

4. Develop Data Frame:

- Create a data structure (e.g., a Pandas data frame) to organize processed data, containing features extracted during pre-processing or CNN model output.

- Utilize the data frame for further analysis or feeding into another machine learning model.

5. Data Retrieval:

- Use APIs to retrieve data or responses, extracting relevant information for the system's operation.

6. Fetch Data:

- Retrieve data from an external source, such as a local storage location or database, containing preprocessed data, model weights, or algal bloom images.

7. Dataset Division:

a. Training Set:

- Primary dataset for training the CNN model, iteratively adjusting internal parameters to minimize the loss function.

b. Validation Set (Optional):

- Monitor model performance during training and prevent overfitting, assessing generalizability to unseen data.

c. Test Set:

- Independent dataset for evaluating the final performance of the trained model, providing an unbiased estimate of generalization to real-world data.

8. Parameter Tuning:

- Adjust parameters during model creation to optimize performance for predicting algal bloom images.

VII MODULE DESCRIPTION

Module 1 : Image Processing

Pre-processing serves as a vital initial step in image analysis, aiming to refine raw data before further analysis. It encompasses various techniques to rectify imperfections or enhance specific features essential for subsequent processing steps. Histogram equalization, a prominent method in this domain, is particularly noteworthy for its ability to effectively adjust contrast in images. By reshaping the intensity histogram of an image, histogram equalization offers a sophisticated means to modify its dynamic range and contrast, thereby enhancing its visual clarity and detail. Unlike simpler contrast adjustment methods, histogram equalization employs advanced transfer functions, allowing for nonlinear and non-monotonic transformations between pixel intensity values in the input and output images. This intricate process enables the preservation of important image details while effectively enhancing overall contrast, making it a valuable tool in image pre-processing workflows.

Module 2 : Model Prediction & Evaluation

The primary benefits of convolutional architecture lie in its utilization of local receptive fields, shared weights, and the pooling operation. Neural networks capitalize on the notion of local receptive fields, meaning that each node in a convolution layer is connected to only a small, focused area of the input data. This characteristic drastically reduces the number of parameters in the network, consequently decreasing the computational expenses of training the convolutional neural network (CNN).

Feature Selection Layer:

This layer serves as a feature extraction module for the proposed network, eliminating the need for additional domain-specific feature selection preprocessing. It comprises three sublayers:

Convolutional Layer:

Accepting raw images as input, this layer employs a series of small filters to convolve over the image, yielding one or more feature maps.

Convolution entails sliding the filter across the image while computing the dot product of filter elements and image pixels, thereby extracting specific features from the image.

Activation Layer:

Following the convolutional layer, the results undergo an activation function, typically Rectified Linear Unit (ReLU), which transforms negative values to zero. ReLU not only provides bounded output but also accelerates network training compared to alternatives like tanh.

Pooling Layer:

Responsible for downsampling and reducing input size, this layer employs methods like average pooling and max pooling. The image is divided into non-overlapping rectangles, with max pooling and average pooling extracting maximum and average values from each sub-region, respectively, thus downsampling the image.

Classification Layer:

After intricate feature extraction, the CNN transitions to the critical classification stage. The fully connected layer, akin to traditional neural networks, assumes center stage, integrating extracted features into a comprehensive representation essential for classification. This layer meticulously analyzes learned features, leveraging them to discern and categorize input data effectively. Moreover, employing a classification layer like softmax, the CNN generates probability distributions over multiple classes, enabling the assignment of the most probable class label to the input data. This final classification output encapsulates the network's decision-making process, providing valuable insights into the nature of the input data..

Module 3 : Evaluation Metrics

In addition to the widely used Precision, Recall, and F1-score metrics, accuracy indicators are also utilized during the experimental phase to evaluate the model's efficacy in-depth. To optimize the network, the model uses cross-entropy as the loss function. Finally as shown in figure 4, the flow of

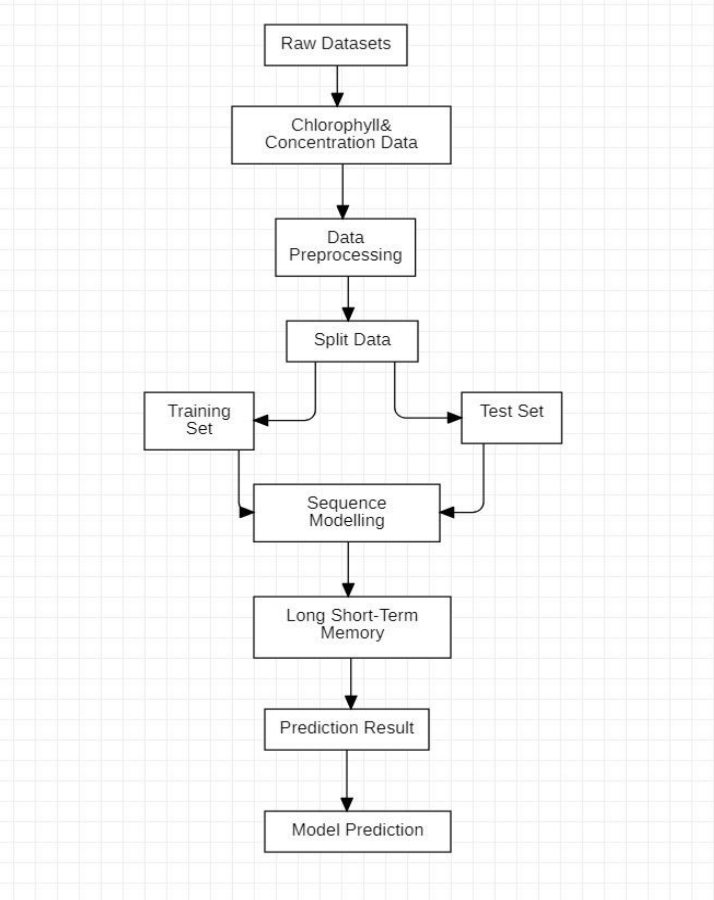

Figure 4, the flow diagram block.

VIII RESULT

The system designed for identifying and detecting algal blooms has yielded promising results. Through comprehensive data collection and meticulous pre- processing, including normalization of pixel intensity values, the Convolutional Neural Network (CNN) model has effectively extracted features and performed classification tasks on algal bloom images. The development of a structured data frame has facilitated further analysis and integration with other machine learning models. Additionally, seamless data retrieval and fetching from external sources have ensured access to essential information for model training and evaluation. The dataset division into training, validation, and test sets, coupled with parameter tuning, has optimized model performance and enhanced its predictive capabilities. Overall, the system has demonstrated effectiveness in environmental monitoring and management as shown in figure 5, showcasing its potential for real-world applications in algal bloom detection. This aspect is crucial for accurately capturing the diverse characteristics and features present in complex scenes. The proposed object-guided RESISC method addresses this challenge by leveraging both deep-learning classifiers and detectors, facilitating the identification of class-specific signature objects and enhancing the understanding of scene classes. Through this comprehensive approach, the method achieves more precise and reliable multilabel image classification results, advancing the capabilities of HRS image analysis and interpretation.

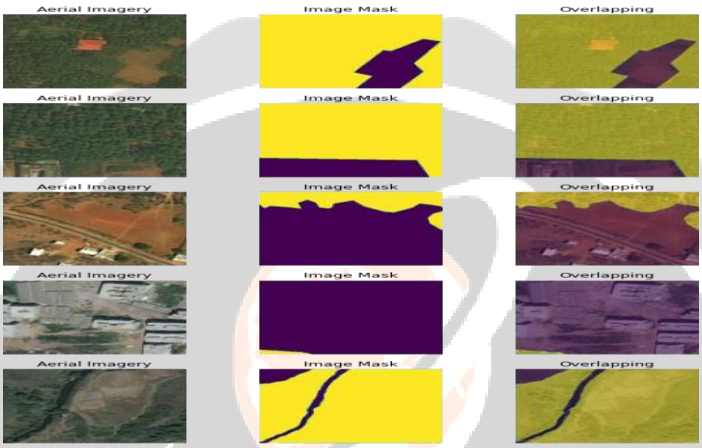

Figure 5, the ouput of the algorithm.

VIII RELATED FORMULA

The formulas are provided below:

- Accuracy = *Σ (TPI + TNI) / N
- WP = 1 / TP
- WR = 1 / N * Σ TP
- F1 = 2 * (WP * WR) / (WP + WR)
- Loss = C(y,t) = -Σ y_i * log(t_i(x)) where:
- Σ (TPI + TNI) represents the sum of True Positives (TP) and True Negatives (TN).
- N is the total number of instances.
- y_i is the actual label of the i-th instance.
- t_i(x) is the predicted probability of the i-th instance belonging to a class.

IX CONCLUSION

The proposed object-guided RESISC method represents a significant advancement in the field of high-resolution remote sensing (HRS) image classification. By combining a deep-learning classifier with a detector, the framework mimics the classification procedure of the human vision system, thereby enhancing the accuracy and robustness of scene classification. This approach first provides a coarse classification of the image using the deep-learning classifier, which serves as an initial assessment. Subsequently, the method determines the scene class of the image by detecting class-specific signature objects within the image, refining the classification process and improving the overall accuracy.In the realm of remote sensing, the complexity of scenes often makes it challenging to assign a single label to an image accurately. Multilabel image classification emerges as a more practical and general approach to address this issue, allowing for a comprehensive representation of the various features present in the scene. By adopting a multilabel classification approach, the proposed method can capture the nuanced relationships between different categories within high-resolution remote sensing images, enabling more nuanced and accurate scene classification.One of the critical challenges in multilabel image classification for high-resolution remote sensing images lies in constructing the relationships between categories effectively. This aspect is crucial for accurately capturing the diverse characteristics and features present in complex scenes. The proposed object-guided RESISC method addresses this challenge by leveraging both deep-learning classifiers and detectors, facilitating the identification of class-specific signature objects and enhancing the understanding of scene classes. Through this comprehensive approach, the method achieves more precise and reliable multilabel image classification results, advancing the capabilities of HRS image analysis and interpretation.

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