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Extraction of Water Bodies from Remote Sensing Data using Machine Learning

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Abstract: Water body identification and monitoring are crucial in Earth observation and environmental monitoring efforts. These bodies, including natural lakes, rivers, reservoirs, and human-made ponds, hold significant ecological and practical value, impacting ecological balance, resource management, and disaster risk reduction. While methods like NDWI and MNDWI have been traditional tools for delineating water bodies from satellite data, the rise of machine learning offers new avenues for accuracy enhancement. This project focuses on using machine learning for water body extraction from remote sensing data, aiming to improve detection accuracy beyond traditional methods. Through model evaluation, the study seeks to advance current practices, benefiting resource management, environmental conservation, and disaster readiness. The trained model shows steady improvement over 60 epochs, starting with an accuracy of 63.39% and a loss of 0.5331 in the first epoch, eventually reaching approximately 81.14% accuracy and a loss of 0.1505 by the final epoch. This progression indicates the model's ability to learn and adapt, capturing underlying data patterns effectively. Validation accuracy also increases consistently, reflecting the model's ability to generalize well. The convergence of training and validation metrics signifies the model's stability and reliability in making predictions on unseen data.

Index Terms **- Water body extraction, machine learning, remote sensing, deep learning, environmental monitoring.**

I.INTRODUCTION

The system introduces the critical role of water bodies within Earth observation and environmental monitoring. Leveraging traditional methodologies like the NDWI and MNDWI has laid the groundwork for water body delineation from satellite data, yet the emergence of machine learning techniques presents opportunities for refinement. The objective is to harness these advanced approaches to surpass the limitations inherent in traditional methods by utilizing deep learning and image analysis. Through the evaluation of diverse models, the study seeks to propel discussions on enhancing water body detection accuracy, ultimately advancing resource management, environmental sustainability, and disaster preparedness.

This endeavor holds transformative potential, potentially reshaping Earth observation and environmental assessment practices by providing more precise data for crucial decision-making processes. The primary aim is to exploit these advanced approaches to surpass the limitations inherent in traditional methods by incorporating deep learning and image analysis into the water body delineation process. The integration of machine learning holds promise for enhancing the precision and accuracy of identifying water bodies from satellite imagery. Through a comprehensive evaluation of various models, the study seeks to stimulate conversations and contribute insights that can elevate the accuracy of water body detection.

II.LITERATURE REVIEW

This section provides an overview of relevant prior work in water body identification.

[1], the normalized difference water index (NDWI) was modified by substitution of a middle infrared band such as Landsat TM band 5 for the near infrared band used in the NDWI. The modified NDWI (MNDWI) can enhance open water features while efficiently suppressing and even removing built-up land noise as well as vegetation and soil noise. The enhanced water information using the NDWI is often mixed with built-up land noise and the area of extracted water is thus overestimated. Accordingly, the MNDWI is more suitable for enhancing and extracting water information for a water region with a background dominated by built-up land areas because of its advantage in reducing and even removing built-up land noise over the NDWI.

[2], Mosquito-borne diseases affect millions of people worldwide. In the United States, since 1999, West Nile Virus (WNV) has infected 36,801 people and has caused the deaths of 1,580. In California, since 2002, nearly 3,600 people have been infected with WNV with an additional 124 fatalities. Analyses of remotely- and spatially-based data have proven to facilitate the study of mosquito-borne diseases, including WNV. This study proposes an efficient procedure to identify swimming pools that may serve as potential mosquito habitat. The procedure derives the Normalized Difference Water Index (NDWI) from high resolution, multi-spectral imagery to detect the presence of surface water, and then incorporates vector-based data layers within a GIS to identify

residential land parcels with detectable water. This study compared the parcels identified as having water (535) with parcels known to have swimming pools (682) resulting in an accuracy of 78.4%. Nineteen of the 147 land parcels with swimming pools had backyards with enough vegetation to obscure the presence of a swimming pool from the satellite. The remaining 128 parcels lacked enough surface water for the NDWI to indicate them as actually having surface water. It is likely then that swimming pools, associated with such parcels, may have enough water in them to provide adequate habitat for mosquitoes, and so field inspection by mosquito abatement personnel would be justified.

[3], Water is crucial in urban environments, and extracting water bodies is vital for planning. Remote sensing is used for this purpose, but it's challenging due to spectral variance and complex ground features in urban areas. This study aims to improve water body extraction from moderate-resolution satellite images using a method combining multiscale extractions and spectral analysis in adaptive local regions. The process involves calculating NDWI from experimental images to select water pixels, applying spectral analysis to determine water abundance, and segmenting the image for global water body extraction. The method was tested on urban areas using ALOS/AVNIR-2 and Terra/ASTER images, outperforming other methods based on NDWI thresholding and SVM classification.

[4], Timely and accurate pixel-level water surface proportion data from remote sensing is crucial for ecological restoration in inland river basins and precise water resource management. To address the limited extraction of water surface proportion information in current models, an Enhanced Water Index (EWI) model based on Modified Normalized Difference Water Index (MNDWI) has been introduced. EWI focuses on sub-pixel level water surface proportion mapping in inland river basins by analyzing typical spectral signatures like desert, soil, and vegetation along with MNDWI using Landsat TM bands. The model uses pixel-based EWI values with various water proportions via linear hybrid simulation between water bodies and backgrounds. Testing in the Tarim region resulted in an R2 = 0.72 correction coefficient, indicating effective extraction of pixel-level water surface proportion data. This study highlights the EWI model's potential for water proportion mapping applications.

[5], There are regional limitations in traditional methods of water body extraction. For different terrain, all the methods rely heavily on carefully hand-engineered feature selection and large amounts of prior knowledge. Due to the difficulty and high cost in acquiring, the labeled data of remote sensing is relatively small. Thus, there exist some challenges in the classification of huge amount of high dimension remote sensing data. Deep Learning has a good capacity of hierarchical feature learning from unlabeled data. Stacked sparse autoencoder (SSAE), one deep learning method, is widely investigated for image recognition. In this paper, a new water body extraction model based on SSAE is established. At first, current useful features (NDWI, NDVI, NDBI and so forth) are collected to construct unique feature matrix for each pixel. Next, a Feature Expansion Algorithm (FEA) is designed by taking account of the influence of neighboring pixels to expand feature matrixes. Setting the expansion features as inputs, SSAE is trained to extract water body. The experimental results showed that the proposed model outperformed Support Vector Machine (SVM) and traditional neural network (NN). Meanwhile, the proposed FEA explored more distinct features of water body so that the accuracy of water body extraction was improved to a great extent.

[6], investigates how boundary pixels of rivers face spectral mixture issues that hinder accurate extraction using traditional classifiers. To tackle this, unmixing and super-resolution mapping (SRM) are conducted in two steps. Optimal band analysis for the normalized difference water index (OBA-NDWI) is proposed to identify bands with the highest NDWI correlation with water fractions. OBA-NDWI incorporates this optimal NDWI as a predictor through regression. Water fractions from OBA-NDWI are compared with simplex projection unmixing (SPU) results. SRM includes pixel swapping (PS) and interpolation-based algorithms. A modified binary PS (MBPS) method reduces computational time. OBA-NDWI results align well with SPU (R2 = 0.9, RMSE = 7% for WV-3, R2 = 0.87, RMSE = 9% for GeoEye). WV-3 bands offer various options via OBA-NDWI. Interpolation-based and MBPS methods produce comparable sub-pixel maps more efficiently than PS. SRM improves accuracy by about 10% over traditional classification.

[7], Water body extraction is an important part of water resource management and has been the topic of a number of research works related to remote sensing for over two decades. Extracting water bodies from satellite images with a pixel-based method or indexes cannot eliminate other objects that have a low albedo, such as shadows and built-up areas. Since their spectral differences cannot be separated, in this paper a method that combines a pixel based index and object-based method has been used on a Sentinel-2 satellite image with a resolution of 10 m. The method uses image segmentation on a multispectral image containing 13 bands. It also uses indexes used for extracting water bodies, such as the Normalized Difference Water Index (NDWI). Two study areas with different characteristics have been chosen, one mountainous and one urban region, both of them located in Macedonia. Using object-based techniques and pixel-based indexes, such as NDWI, the results from the NDWI have been improved by a kappa value of more than 0.5.

[8], Accurate information on urban surface water is important for assessing the role it plays in urban ecosystem services in the context of human survival and climate change. The precise extraction of urban water bodies from images is of great significance for urban planning and socioeconomic development. In this paper, a novel deep-learning architecture is proposed for the extraction of urban water bodies from high-resolution remote sensing (HRRS) imagery. First, an adaptive simple linear iterative clustering algorithm is applied for segmentation of the remote-sensing image into high-quality superpixels. Then, a new convolutional neural network (CNN) architecture is designed that can extract useful high-level features of water bodies from input data in a complex urban background and mark the superpixel as one of two classes: an including water or no-water pixel. Finally, a high-resolution image of water-extracted superpixels is generated. Experimental results show that the proposed method achieved higher accuracy for water extraction from the high-resolution remote-sensing images than traditional approaches, and the average overall accuracy is 99.14%.

[9] Monitoring water bodies via remote sensing is essential for environmental conservation, sustainable development, and various applications. Traditional index-based and deep learning methods have limitations in dealing with large, heterogeneous areas with different water body complexities. This article presents an attentional dense convolutional neural network (AD-CNN) designed specifically for water body extraction from Sentinel-2 imagery. The AD-CNN leverages dense connections to uncover deeper features and a residual attention module to dynamically focus on relevant spatial-spectral features for classifying water pixels. To evaluate its performance, a new water database of Nepal (WaterPAL) is developed. Experimental results demonstrate the competitive performance of the proposed AD-CNN architecture compared to traditional index-based and state-of-the-art deep learning-based water extraction models.

[10] Mapping of surface water is useful in a variety of remote sensing applications, such as estimating the availability of water, measuring its change in time, and predicting droughts and floods. Using the imagery acquired by currently active Landsat missions, a surface water map can be generated from any selected region as often as every 8 days. Traditional Landsat water indices require carefully selected threshold values that vary depending on the region being imaged and on the atmospheric conditions. They also suffer from many false positives, arising mainly from snow and ice, and from terrain and cloud shadows being mistaken for water. Systems that produce high-quality water maps usually rely on ancillary data and complex rule-based expert systems to overcome these problems. Here, we instead adopt a data-driven, deep learning-based approach to surface water mapping. We propose a fully convolutional neural network that is trained to segment water on Landsat imagery. Our proposed model, named DeepWaterMap, learns the characteristics of water bodies from data drawn from across the globe. The trained model separates water from land, snow, ice, clouds, and shadows using only Landsat bands as input.

III.METHODOLOGY

A. Data Collection

During the data collection stage, satellite imagery is gathered from various sources, including Landsat, Sentinel-2, and high-resolution commercial satellites like WorldView-3 and GeoEye. Landsat satellites, managed by NASA and the US Geological Survey, offer multispectral data with spatial resolutions ranging from 15 to 60 meters and a long history of freely accessible imagery. Sentinel-2, part of the European Union's Copernicus program, provides high-resolution multispectral data with resolutions of 10 to 20 meters and frequent revisits, enabling temporal analysis. High-resolution commercial satellites like WorldView-3 and GeoEye offer very detailed imagery with resolutions as fine as 0.3 to 1.5 meters, ideal for precise mapping and monitoring tasks. The data acquisition process involves accessing and downloading these images from official repositories or commercial providers, followed by preprocessing steps like georeferencing and atmospheric correction. Considerations during data collection include spatial resolution, spectral bands for specific analyses, temporal frequency, and image quality criteria such as cloud cover percentages and acquisition dates, ensuring suitability for subsequent analyses such as water body extraction using machine learning techniques.

B. Data Preprocessing

The collected satellite data undergoes essential preprocessing steps to prepare it for further analysis. This process involves several critical procedures, each aimed at enhancing the quality and accuracy of the data.

- Radiometric Calibration: Radiometric calibration corrects for variations in sensor response and illumination conditions. It ensures that pixel values in the imagery accurately represent the reflectance or radiance of the Earth's surface, allowing for meaningful comparisons across different images and time periods.

- Atmospheric Correction: Atmospheric correction is crucial for minimizing the impact of atmospheric effects on the image data. This correction accounts for factors such as aerosols, gases, and water vapor in the atmosphere, which can distort the appearance of features in the satellite imagery. By removing these atmospheric artifacts, the corrected data provides a more accurate representation of surface reflectance.

- Geometric Correction: Geometric correction addresses geometric distortions caused by the satellite's sensor and position. These distortions can include effects like sensor tilt, spacecraft attitude changes, and Earth's curvature. By applying geometric correction techniques, such as orthorectification, the satellite imagery is transformed to align with a known map projection or coordinate system, ensuring accurate spatial representation.

- Image Segmentation: Image segmentation plays a vital role in dividing the satellite image into meaningful segments or regions based on similarities in spectral properties, texture, or other features. This segmentation process helps in identifying distinct objects or areas of interest within the imagery, facilitating subsequent analysis tasks such as object detection, classification, and feature extraction.

C. Training the Model

Here, a machine learning model is trained to identify water bodies in the preprocessed satellite images. There are two main approaches for this stage:

- Traditional Machine Learning: This involves manually selecting features in the image data that are believed to be indicative of water bodies, such as spectral reflectance or texture. Then a classifier algorithm is trained on labelled data sets to learn the relationship between these features and the presence of water. Examples of traditional machine learning algorithms used for water body detection include support vector machines (SVMs) and random forests.

- Deep Learning: This is a more advanced approach that utilizes deep convolutional neural networks (CNNs) to automatically extract features from the image data. CNNs are trained on large datasets of labelled satellite images and can learn complex patterns that distinguish water bodies from other land cover types.

D. Prediction

- Model training involves feeding the machine learning model with a large dataset of labeled satellite imagery. This dataset consists of examples where each pixel is labeled as either "water" or "non-water." The model learns to identify patterns and features that distinguish water bodies from other land cover types during this training phase. After training, the model's performance is evaluated using a separate validation dataset. This evaluation assesses how well the model generalizes to new, unseen data and ensures that it can accurately predict water bodies in different satellite images.
- During the prediction phase, the trained model is applied to new, unseen satellite images to detect the presence of water bodies. The preprocessed image data, which has undergone radiometric calibration, atmospheric correction, and geometric correction, is inputted into the model. The model then processes each pixel in the image and assigns a classification label indicating whether it is likely to represent a water body or not. This process generates a classified image where water bodies are highlighted, allowing for the identification and mapping of water resources across the landscape.

E. Ground Truth Data

- Ground truth data serves as the foundation for training machine learning models by providing precise labels indicating whether specific pixels or regions in the satellite image represent water bodies or other land cover types. This accurate reference data guides the model in learning the distinguishing features and characteristics of water bodies, improving its ability to make accurate predictions.
- During the training process, the machine learning model compares its predictions against the ground truth data to adjust its internal parameters and optimize its performance. Additionally, ground truth data plays a crucial role in evaluating the model's accuracy and reliability, ensuring that it can effectively detect and classify water bodies in new satellite images beyond the training dataset.
- Obtaining ground truth data involves various methods such as acquiring high-resolution imagery with known water body locations, conducting field surveys to validate satellite-based observations, or utilizing existing authoritative datasets from reliable sources. This meticulous data collection process is essential for creating robust and trustworthy machine learning models for water body detection, contributing to informed decision-making in environmental management and resource monitoring initiatives.

F. Comparative Analysis

- After the model has made predictions on new satellite images, the final step involves a comprehensive comparison between these predictions and the ground truth data, which serves as the gold standard for accuracy assessment. This comparison is crucial for evaluating the model's ability to correctly identify water bodies and distinguish them from other land cover classes.
- By comparing the model's predictions with the ground truth data, analysts can determine the model's overall accuracy and effectiveness in detecting water bodies across different landscapes and environmental conditions. This evaluation process provides valuable insights into the model's strengths, weaknesses, and areas for improvement, contributing to ongoing refinement and optimization efforts.
- Performance metrics such as overall accuracy, precision, and recall are calculated based on the comparison between predicted and actual water body locations. These metrics quantitatively measure how well the model aligns with ground truth data, with accuracy indicating the proportion of correctly classified pixels, precision measuring the model's ability to avoid false positives, and recall evaluating its capability to detect true positives, all essential aspects in assessing the model's performance robustness.

IV.RESULTS

The primary objective of our project is to evaluate the performance of a water body segmentation system using the UNet model. Key factors under consideration include accuracy, computational efficiency, and scalability, with a focus on providing reliable segmentation results for environmental monitoring and conservation efforts.

Accuracy: The model trained over 60 epochs exhibits a progressive improvement in accuracy and loss metrics. Starting with an accuracy of around 63.39% and a loss of 0.5331 in the first epoch, it gradually enhances its performance. By the final epoch, the accuracy reaches approximately 81.14%, with a loss reduced to 0.1505.

Computational Efficiency**:** The UNet model demonstrated efficient performance, with an average inference time of 0.5 seconds per image on a standard CPU.

Scalability**:** The UNet model exhibited scalability, successfully segmenting water bodies in large-scale satellite imagery datasets without significant degradation in performance.

V.CONCLUSION

In conclusion, the project signifies a significant advancement in the field of remote sensing and environmental monitoring by harnessing machine learning techniques for water body extraction. The successful development and evaluation of machine learning algorithms utilizing deep learning and image analysis present promising avenues for enhancing the accuracy and efficiency of detecting diverse water bodies from remote sensing data. The applications stemming from this project span various critical domains, including environmental conservation, resource management, disaster response, urban planning, ecological studies, and climate change analysis. By providing precise and timely information about water bodies, the project stands to revolutionize decision-making processes, aiding in sustainable resource management and proactive disaster mitigation. The project's outcomes pave the way for future innovations in Earth observation, emphasizing the crucial role of technology in fostering a deeper understanding of our ecosystems and their vulnerabilities in the face of global environmental challenges.

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