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Detection of Water bodies using Satellite Imagery based on Deep Learning

Dr. Rajkumar L. Biradar[1], Sowmya Thatipalli[2], Akhila Mucharla[3], Sathvika Adepu[4], Pujitha Mandava[5]
[1]Professor& HOD, [2, 3, 4, 5]UG Scholar, Department of Electronics and Telematics G. Narayanamma Institute of Technology and Science,Shaikpet, Hyderabad.

Abstract: Satellite images are important for monitoring and managing natural resources. Water bodies such as lakes, rivers, and oceans are of great importance to the environment and human populations. The identification of water body pixels in satellite images is therefore an important task for environmental management and planning. In recent years, deep learning has shown great promise in image processing, including object detection and segmentation. This study employs CNNs and RNNs to identify water body pixels in satellite images, aiming to create a model that can accurately distinguish water and non-water pixels. This model has practical applications in environmental monitoring and management.
Keywords: Machine learning; CNN; SVM, Water Body Identification; Satellite Images.

I. INTRODUCTION

Detecting water bodies in satellite images is a pivotal challenge with far-reaching implications across numerous domains, including urban planning, disaster mitigation, and environmental surveillance. Historically, this identification has been mostly dependent on techniques like manual visual interpretation and the use of spectra.

indices. However, these conventional techniques tend to be time-intensive, laborious, and susceptible to human error. In a marked departure, deep learning techniques present a revolutionary approach, offering automation and significantly heightened accuracy.

The primary aim of this endeavor is to create a sophisticated model specifically designed to identify water bodies within satellite imagery automatically.. The potential implications of such a model are far-reaching, encompassing the monitoring of vital water resources, the precise identification of alterations in water bodies, the strategic planning of flood control measures, and the evaluation of the far-reaching consequences of climate change on aquatic systems.

Deep learning brings a host of advantages to the table when applied to water body identification. Its automated nature expedites the process, eliminating the need for extensive human intervention and reducing time consumption. Moreover, it substantially curtails the subjectivity inherent in manual interpretation, ensuring consistent and objective results. Furthermore, the scalability of deep learning algorithms equips them to handle voluminous datasets and facilitates the continuous monitoring of water body dynamics and changes over time. This synergy between the efficiency of deep learning and the wealth of available satellite data promises valuable insights into water body distribution and behavior, ultimately enhancing the management of environmental resources, urban planning, and hydrological research through more accurate and efficient means of detection of the water body in satellite pictures.

II. RELATED WORK

The science of deep learning and computer vision has advanced significantly in the last few years, which has resulted in the creation of effective and automated techniques for identifying water bodies. Deep learning, a subset of machine learning, has sparked a paradigm shift in pattern recognition and image processing through its utilization of multi-layered artificial neural networks. Deep learning offers significant advantages over manual interpretation in the identification of water bodies. It is faster and more automated, saving time and effort on the part of the human operator. Furthermore, by removing subjective biases, deep learning models have the potential to achieve improved accuracy and consistency. Additionally, their scalability enables the analysis of extensive datasets and the long-term monitoring of water body dynamics. the power of deep learning algorithms, capable of analyzing complex patterns and extracting meaningful features from satellite imagery, this project aims to develop a robust model for automatic detection and characterization of water bodies.

Numerous research endeavors water body identification from satellite imagery, employing a diverse array of methodologies and techniques.. One study employed color component analysis and morphological operations, achieving an accuracy of 76.97% [1].

Another study introduced a hybrid approach combining support vector machines (SVM) and multi-instance learning (MIL), with an overall accuracy of 91.24% for urban building classification [2]. Additionally, deep learning and convolutional neural networks (CNNs) were used to segment and detect objects in satellite images, highlighting the effectiveness of CNNs in image classification [3]. Furthermore, an automated approach utilizing the Faster R-CNN algorithm achieved high accuracy in extracting water bodies from satellite images, with 98.7% accuracy for Sentinel-2 data and 96.1% accuracy for Landsat-8 data [4]. Lastly, a a deep learning-based method with 70% precision and 90% accuracy that used convolutional neural networks (CNNs) to locate water bodies [5]. These studies demonstrate the diverse approaches and impressive accuracies achieved in water body identification and classification from satellite imagery.

Systems that are now in use for identifying water bodies in satellite pictures include algorithmic, supervised, and unsupervised methods. Some common methods include matched filtering, utilizing Gaussian intensity profiles, morphological transformations involving erosion and dilation, and model-based algorithms using predefined water body templates for identification. Edge detection methods and global thresholding algorithms are also employed to delineate water boundaries and segment images effectively.

III. METHODOLOGY

The proposed method represents a paradigm shift in the field of water body detection from satellite imagery, offering a holistic approach that integrates cutting-edge deep learning techniques with established machine learning principles. This all-encompassing approach seeks to produce a water body identification procedure that is reliable and highly accurate for a variety of satellite imagery. The incorporation of classic machine learning models like Random Forest and Support Vector Machine (SVM) into the system introduces crucial features that enhance its overall performance and robustness. Random Forest, as an ensemble learning technique, excels in handling high-dimensional data and capturing intricate relationships within the data. This method constructs a multitude of decision trees during the training phase, each tree trained on a random subset of the data and features. This makes it a versatile choice for recognizing various water body shapes and patterns commonly encountered in satellite imagery. Its adaptability to different water body characteristics contributes significantly to the system's versatility and effectiveness.

SVM, another cornerstone of this system, is a powerful classification algorithm renowned for its applicability in both linear and non-linear classification tasks. By integrating SVM, the system gains the ability to address a wide spectrum of water body shapes and sizes. This ensures a comprehensive and accurate identification process, as SVM excels in handling complex and diverse data patterns. Complementing these traditional machine learning techniques are advanced deep learning models, specifically FCN (Fully Convolutional Network) and U-Net. FCN specializes in semantic segmentation, making use of convolutional layers to capture not only spatial information but also contextual cues within the satellite imagery. This enriches the precision of delineating water bodies, ensuring that intricate details and boundaries are accurately identified.

U-Net, initially designed for biomedical image segmentation tasks, has emerged as a pivotal architecture for preserving intricate spatial details and boundaries, making it highly relevant for various image analysis tasks, including satellite image processing. One of the key features that distinguishes U-Net is its utilization of skip connections, which facilitate the seamless integration of fine-grained details from early convolutional layers with higher-level feature representations.

This is particularly valuable when dealing with complex and irregular water bodies that exhibit diverse shapes and sizes. By synergizing the unique strengths of each model, this hybrid approach maximizes the system's overall performance, offering a reliable and accurate solution for automating the crucial task of water body identification in satellite imagery. By integrating advanced deep learning techniques with classic machine learning models, the proposed approach not only enhances the accuracy and efficiency of water body detection in satellite imagery but also offers significant benefits across diverse domains such as environmental monitoring and disaster management. The system stands as a state-of-the-art solution geared towards substantially elevating the precision and efficiency of water body identification within satellite images.

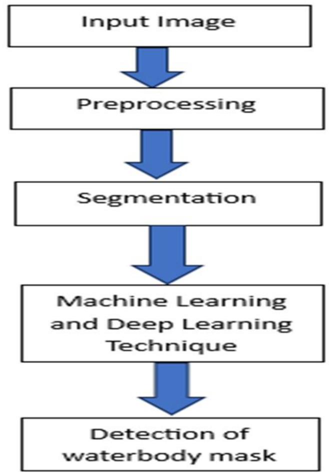

Fig 3.1: Methodology

The above figure shows the Methodology involves data preprocessing, segmentation, model training, detection of waterbody mask.

IV. RESULTS AND DISCUSSION

The Sentinel-2 Satellite collected 2,841 satellite photos for the dataset, along with the corresponding masks for each image. A black and white mask is included with each image, with black denoting non-water parts and white representing water. The Normalized Water Difference Index (NWDI), a commonly employed tool for detecting and quantifying vegetation in satellite imagery, was repurposed for generating masks in this endeavor.To precisely identify water bodies in this instance, a higher threshold was used.

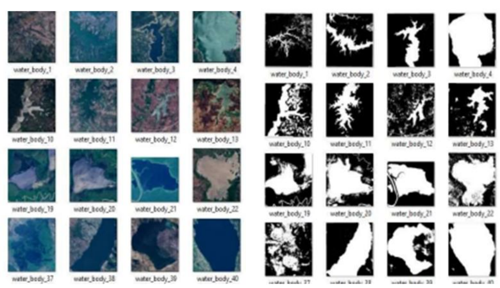

Fig-5.1 Dataset

The above figure shows input images and their respective masks.

We conducted experiments using a dataset of 2,841 satellite images and their accompanying masks in order to assess the efficacy of the proposed system. The dataset partitioning into training, testing, and validation sets, employing a judicious ratio of 75:25:1.5, respectively.

The images and masks were resized to 256x256 pixels and normalized to a range of 0-1. We implemented and trained four models: Random Forest, SVM, FCN, and U-Net, using Python and TensorFlow. The performance evaluation of the developed models involved a comprehensive comparison based on various metrics, including accuracy, precision, recall, and segmentation metrics..

The Random Forest model demonstrated promising performance, achieving an accuracy of 75.45% and a precision of 0.7508 on the test set. The confusion matrix provides detailed insights into the performance of the model by presenting a breakdown of correct and incorrect classifications. In this case, the model correctly classified 1,012 water pixels and 1,050 non-water pixels. However, it also misclassified 331 water pixels as non-water and 339 non-water pixels as water.

On the test set, the SVM model exhibited an accuracy of 69.72% and a precision of 0.7846.. Upon examination of the confusion matrix, it is evident that the model correctly classified 1,052 water pixels and 857 non-water pixels. However, it misclassified 291 water pixels as non-water and 532 non-water pixels as water.

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After undergoing 60 epochs of training, the Fully Convolutional Network (FCN) model exhibited promising performance metrics on the test set. With an accuracy of 72.47% and a loss of 0.3235, the model demonstrates its capability to effectively identify water bodies within satellite imagery. The model also achieved a mean intersection over union (MIoU) of 0.6247 and a dice coefficient of 0.7649 on the test set. These metrics indicate the quality of the segmentation masks generated by the model. After 60 epochs of training, the U-Net model achieved an accuracy of 86.93% on the test set, indicating its ability to effectively classify pixels as water or non-water. Moreover, the U-Net model attained a mean intersection over union (MIoU) of 0.7412 on the test set, reflecting a significant overlap between the predicted segmentation masks and the ground truth masks. The results are somehow show that the U-Net model outperformed the other models in terms of metrics, loss, MIoU, and dice coefficient, demonstrating its effectiveness in identifying and segmenting water body's from satellite images. The FCN model also performed well in terms of segmentation metrics, but had lower accuracy and higher loss than the U-Net model. The Random Forest and SVM models had lower accuracy and precision than the deep learning models, indicating their limitations in capturing complex spatial features and variations in water body shapes and sizes.

Table-1: Comparison of Accuracy of the models

Model	Epoch	Accuracy	Precision
Support Vector Machine	-	69.72%	0.7846
FCN	20	72.33%	0.3644
	40	72.44%	0.3238
	60	72.47%	0.3235
U-Net	20	83.05%	0.3973
	40	85.29%	0.3729
	60	86.93%	0.3574

The prediction results were visualized using segmentation maps, where each pixel was colored according to its predicted class (water or non-water). The maps clearly showed the locations and shapes of water bodies in the satellite images

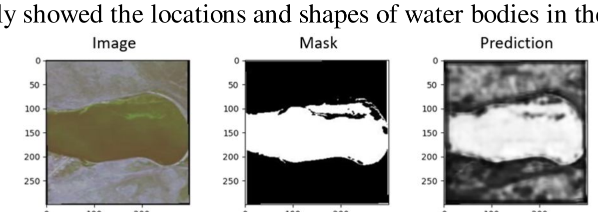

Fig-4.1: Prediction of the Satellite images using FCN model

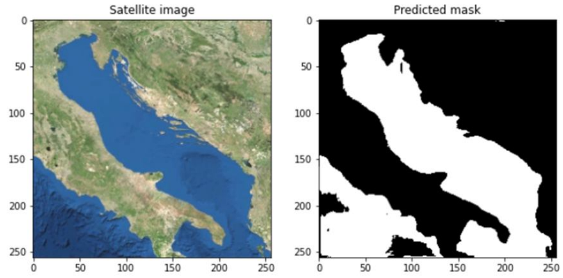

Fig-4.2: Prediction of the Satellite images using U-Net model

V. CONCLUSION

In conclusion, the integration of traditional machine learning models like Random Forest and Support Vector Machine (SVM) with state-of-the-art deep learning models such as Fully Convolutional Network (FCN) and U-Net has yielded promising results in the task of identifying water bodies from satellite imagery.

The models each contribute their unique strengths, with traditional models excelling in handling complex data relationships, and deep learning models showcasing their prowess in capturing spatial details and boundaries. This comprehensive approach offers a robust and efficient solution that holds great potential for diverse applications, from environmental monitoring to disaster management.

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