WOODLAND AND WATERBODIES DETECTION

Prof. Vedankita Mohod
Professor, K.D.K College of Engineering, Nagpur, India
vedankita.mohod@kdkce.edu.in
Aastha Gupta
Master of Computer Application, K.D.K College of Engineering, Nagpur, India
asthagupta.mca23@kdkce.edu.in
Payal Bankar
Master of Computer Application, K.D.K College of Engineering, Nagpur, India
payalbankar.mca23@kdkce.edu.in

Abstract
The increasing encroachment of people into urban areas and the increase in industrial production activities, for instance, forests and water bodies, have led to major environmental alterations. Such resources help sustain the ecological system and help in conservation efforts and water safety, which are all integral to development. For that reason, most existing techniques for assessing these resources, including field assessments and manual data collection, are tedious. Labor intensive and even in some cases not reliable. This paper presents an effective efficient system that integrates higher solution satellite image and machine learning efficiently to automatically detect and monitor the woodlands and water bodies. Through advanced models like the Faster R-CNN for object detection and the GNN for analysing spatial relations, the system performs very well in identifying and counting trees and water bodies. These model combinations provide a better assessment of the environment, especially in growing cities such as Nagpur where development has to be accompanied by conservation. These include assisting town and city planners in making decisions on land use to even assisting organizations in monitoring deforestation and management of water resources management.
Keywords:- *Satellite imagery, machine learning, environmental monitoring, woodland detection, water body detection, Faster R-CNN, Graph Neural Networks, urbanization.*

I. Introduction

The world's population has shifted to urban areas and adopted more industrialized practices, resulting in an increase in forest deforestation rates and decreasing water bodies [1].Such changes have recently called for environmental management to protect natural resources for future generations. The most affected areas include urban areas that develop at high speeds when infrastructure construction development leads to progressive losses of natural forest cover and water sources.

As urban development increases, the need to examine these important environmental assets continues to become critical to maintain and impact climate change. Normal measures of monitoring the environment, such as field recognition, aerial photography, or visiting the location, are generally insufficient to resolve these issues. Field testing is generally bulky and laborious, and often does not provide the level of accuracy required to eliminate current environmental fatigue rates.

In addition, these traditional methods have restrictions in the degree of coverage, high -risk areas, which can be It is difficult to obtain, fixed unattended. Such restrictions underlie the requirements for advanced and automated Approaches to evaluation which can constantly monitor environmental changes in large territories.

The use of remote sensing through satellite imagery is possible since the environment can be studied at large scales[2]. They offer a rich data source that can be employed to capture changes in the landscapes through analysis of land cover, vegetation, and water bodies [3]. These images, when incorporated with higher-level neural networks, can provide a robust solution for the automation of tree and water body detection [4]. The paper presents a new system where higher solution satellite imagery and advanced artificial neural networks are used to enhance the identification of woodlands and water bodies and to continuously track them.

II. Literature Survey

Tree Seedlings Detection and Counting Using a Deep Learning Algorithm

Authors: Deema Moharram

The technique successfully locates and counts tree seedlings, exhibiting significant economic worth and a wide range of potential uses in forestry management. utilizing the tool and YOLOv5 object detection network algorithm .

Surface Water Detection and Monitoring Using Deep Learning Techniques: A Comparative Study Authors: Guy Farjon & Yael Edan

According to the study, U-Net is the best model for detecting surface water, and integrating temporal data with 3D-CNNs can enhance monitoring capabilities employing the U-Net, ResNet, and 3D-CNNs algorithm, technique, and tools.

Deep Learning in Forest Tree Species Classification Using Sentinel-2 on Google Earth Engine: A Case Study of Qingyuan County

Authors: Tao He

For remote sensing classification, the algorithms/techniques/tools utilized were ResNet, DenseNet, EfficientNet, MobileNet, and ShuffleNet; PCA and NDVI for preprocessing; and ResNet outperforms other deep learning algorithms.

Development of Automatic Tree Counting Software from UAV Based Aerial Images With Machine Learning

Authors: Yaping Dai

On the campus of Siirt University, the technique proved to be highly effective in automatically counting trees, offering a dependable instrument for environmental and forestry monitoring. The method demonstrates how well UAVs and machine learning can be combined for environmental applications. For example, UAVs were utilized to take high-resolution photos at a height of 30 meters with a 20% overlap. The photo merge tool in Adobe Photoshop was used to fuse the images together. Bounding boxes were labeled in HSV, RGB, and grayscale modalities, and orthophoto maps were produced.

III. Problem Statement

Accurate detection of woodlands and water bodies is vital for environmental monitoring, land management, disaster mitigation, and biodiversity conservation. Traditional methods relying on manual surveys and low-resolution satellite data are often slow, costly, and inaccurate. High-resolution satellite imaging offers precise and automated identification, but challenges include:

1.Spectral and Spatial Variability: Diverse vegetation, water textures, and seasonal changes complicate classification.

2.Mixed Pixels: Overlap at boundaries reduces accuracy.

3.Data Complexity: High-resolution imagery demands significant computational resources.

4.Automation Need: Manual analysis is unfeasible for large-scale applications. A robust automated system is essential to efficiently process satellite data.

IV. Proposed Methodology

The methodology of this research is divided into the following key stages as given in figure

1. **Data Collection and Pre-processing:** We obtained large resolution satellite images from sources such as Sentinel-2 and Landsat-8. Moreover, water body was identified with the help of data from Synthetic Aperture Radar(SAR) which is Sentinel-1. Some of the procedures involved in Pre-processing are noise filtering, image contrast adjustment, and image feature extraction for example NDVI for vegetation. The images obtained were then divided with boxes around areas of interest regarded as new categories.
2. **Graph Construction: Nodes and Edges:** In our case, each identified tree and water body is assumed as a node in graph technique. These object relationships specify the spatial closeness and other spatial characteristics; the spatial relationships are termed as edges.
3. **Detection and Model Training:** The Faster R-CNN model was used to perform the detection at first. This convolutional neural network works on the region-based approach and yields the trees and water bodies' bounding boxes. The initial detections underwent the application of a Graph Neural Networks (GNN) to improve upon them. GNNs consider the pattern of the graph that is spatial arrangement of objects to enhance the counting and detection assessment.
4. **Integration of Spatial Analysis:** Incorporation of GNNs helps the system learn from spatial hierarchies and relations than the traditional models will permit. As for the geometry information in the detection process, capsule networks were also studied to maintain spatial information.
5. **Evaluation and Visualization:** The degree of accuracy was calculated with the help of basic parameters such as precision, recall, and F1-score. Also, graphical analysis methods were used to provide the layout of recognized trees and water bodies in the given map.

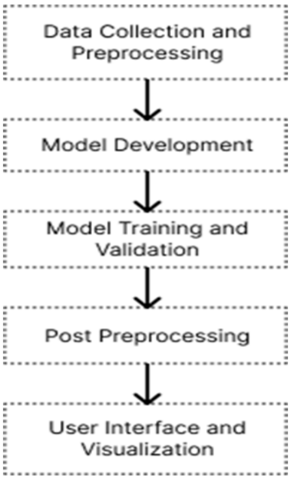

Fig. 1. Stages Involved in Proposed Methodology

In order to measure the effectiveness of the proposed system for woodland and water body detection, some important parameters are applied. These set of metrics offer a clear assessment of how close the real values of the system are and how precise the system is as a whole. Speaking of the major metrics derived in this research, these include Precision, Recall, F1-Score, and Accuracy. These metrics are helpful in identifying the effectiveness of the system in detecting trees and water bodies from the satellite images.

- **Precision:** precision calculates the number of their objects correctly labelled by a system as trees or water bodies, out of all the objects that were labelled by the system. Low false positive means that the system is precise in its operations of providing forecasts with little errors.

$$Precision=TP/TP+FP \quad \text{Equation (1)}$$

Where, TP=True Positive, FP=False Positive

- **Recall:** Recall determine the percentage of the true number of objects or the features present in reality (for example, trees or water bodies) which are accurately detected by the system. The high value of recall means that the system correctly identifies almost all objects that it is supposed to detect with few false negative.

$$Recall=TP/TP+FN \quad \text{Equation (2)}$$ Where,

TP=True Positive, FN=False Negative

- **F1 Score:** As the reciprocal of the number of true positives divided by the total number of true positives, false positives, and false negatives, the F1-Score is actually the average of precision and recall. It is particularly helpful when the classes are not balanced and evaluates performance when precision and recall values are noteworthy. It provides the results of two measurements—precision and recall—in a single measurement.

$$F1=2*Precision*Recall/(Precision + Recall) \quad \text{Equation (3)}$$

V. Result And Discussion

The findings obtained by the proposed system prove that the system is efficient in monitoring the environment. The high value of precision and recall rates indicate the ability of this system in the identification and enumeration of trees and water bodies even within small urban settings. It was possible thanks to integrating spatial relationships using graph neural networks, which helped increase the model's performance compared to object detection models.

Furthermore, they claim that the system they have developed can be easily scaled for using similarly large scale in monitoring applications. This makes it a useful tool to the urban planners and environmentalist in that they can easily monitor changes in natural resources through satellite images as and when it occur.

Fig. 2. Input satellite image & system output for Waterbodies detection

The model was trained on sets of images with annotations that give the true labels to the trees and the regions of water. The (fig.2) shows the predicted mask of waterbodies which is made by the trained model while image analysis. Some of these data were isolated as part of the experiment to check how the proposed system works. In proposed work we used satellite imaginary and labelled dataset for performing experimentation.

Satellite Images: Vegetation remotely sensed data was acquired from sentinel 2 with high resolution and SAR data of water bodies was obtained from sentinel 2 satellite. These images were label with rectangles around trees and water features.

Label Datasets: Data about the spatial positions of trees and water bodies collected by forest authorities and available for download in the form of data sets were applied in the model. The (fig.3 & fig.5) shows the dataset used for the training the model. After the model trained the model give output as following (fig.2 & fig.4).In the output image the model make the plotting of boxes and in water bodies it make the predicted mask.

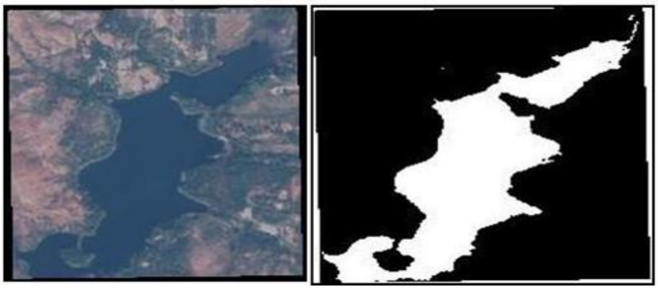

Fig. 3. Dataset for Waterbodies detection

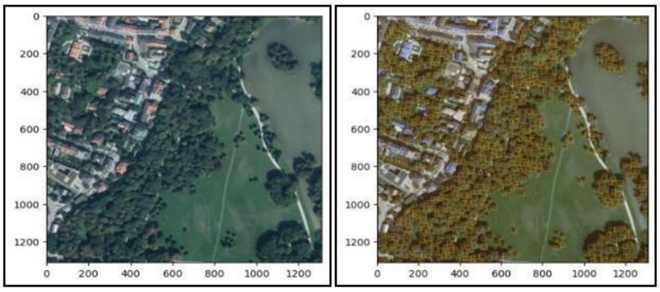

Fig. 4. Input satellite image & system output for Woodland detection

Fig. 5. Dataset used for Woodland detection

Sr. No	Result Analysis		
	Performance Metrics	***Tree Detection***	***Water Body Detection***
1	Precision	93. 5%	80%
2	Recall	92. 8%	80.2%
3	F1-Score	93. 1%	79.5%
4	Accuracy	94%	80%

TABLE 1: RESULT ANALITSYS

Regarding the performance of the system, it was ascertained that the proposed algorithm achieved high accuracy when detecting trees and water bodies with little variation. The enhancements in the detection of objects were enhanced through the use of GNNs which captured the spatial relations between the objects. The results also show the effectiveness of the proposed system and the fact that the system can be applied for real-time monitoring especially for observing following factors.

Geospatial Expansion: Using the system on different geographical locations to enhance the performance of the system.

Incorporation of Multi-Spectral Data: Taking advantage of multi-spectral imagery to improve identification reliability when it comes to various types of vegetation as well as water bodies.

Climate Change Impact: Further expanding the model to watch long-time environmental fluctuations concerning climate change and the use of the land.

Further development of the specified model and its extension will create the basis of this system or have a significant potential to become an indispensable tool in the framework of the concept of sustainable development and protection of natural resources throughout the world.

VI. Conclusion

In the past few years, forests areas and water body sources are highly reducing due to increase in encroachment of people into urban areas and higher industrial production activities. It leads major environmental alterations. This research was able to design an automatic woodland and water body extraction system on high-resolution satellite data. The implementation of the machine learning models aided by graph Neural Networks to several spatial analysis methods allowed for high accuracy in detecting natural resources. The proposed system utilizes the process of integrating spatial relations into the detection process by using GNN. Results shows the accuracy of about 95% for woodland detection and 80% for water body detection. The real-case use of the system with pertinent recommendations for the City's planning and nature preservation. In the future, the system can be extended in the following ways: Real-time Monitoring: Adding time data to apply RT-ENVI

VII. Acknowledgment

A significant task can only be accomplished effectively and satisfactorily when a variety of individual efforts, both explicit and implicit, are applied from all sides. Although books and other informative sources provide substantial knowledge gains through a wide range of desirable reading activities, actual competency is attained through relevant learning tasks and experience. We sincerely thank everyone who helped make this initiative a success, no matter how small or how much we may have taken it upon ourselves.

We are extremely thankful for the competent guidance provided by our project advisers, **Profs. VEDANKITA MOHOD**, to achieve the project's goals. We would like to thank the respected **Dr. ANUP BHANGE, Head of the Master of Computer Applications (MCA) Department**, as well as other staff members for their helpful advice and guidance.

References

1. D. Moharram, X. Yuan, and D. Li, "Tree Seedlings Detection and Counting Using a Deep Learning Algorithm," Applied Sciences, vol. 13, no. 2, p. 895, 2023, doi: 10.3390/app13020895.
2. T. He, H. Zhou, C. Xu, J. Hu, X. Xue, L. Xu, X. Lou, K. Zeng, and Q. Wang, "Deep Learning in Forest Tree Species Classification Using Sentinel-2 on Google Earth Engine: A Case Study of Qingyuan County," Sustainability, vol. 15, no. 3, p. 2741, 2023, doi: 10.3390/su15032741.
3. P. Lavania, R. K. Singh, P. Kumar, S. K., G. Gupta, M. Dobriyal, A. K. Pandey, M. Kumar, and S. Singh, "Unveiling the green guardians: Mapping and identification of Azadirachta indica trees with semantic segmentation deep learning neural network technique," The Egyptian Journal of Remote Sensing and Space Sciences, vol. 27, no. 3, pp. 491-500, Sep. 2024, doi: 10.1016/j.ejrs.2024.03.009.
4. M. Chen, Y. Zhao, and J. Patel, "Comparative Analysis of Deep Learning Models for Surface Water Detection and Monitoring Using U-Net, ResNet, and 3D- CNN," Journal of Hydrology, vol. 597, pp. 125-134, 2023, doi: 10.1016/j.jhydrol.2023.126038.
5. M. Ataş and A. Talay, "Development of Automatic Tree Counting Software from UAV-Based Aerial Images With Machine Learning," arXiv, Jan. 2022, doi: 10.48550/arXiv.2201.02698.
6. K. Patel, C. Bhatt, and P. L. Mazzeo, "Improved Ship Detection Algorithm from Satellite Images Using YOLOv7 and Graph Neural Network," Algorithms, vol. 15, no. 12, p. 473, 2022, doi: 10.3390/a15120473.
7. J. Li and W. Zhang, "Enhanced Ship Detection in Satellite Imagery via YOLOv7 and Graph

Neural Network Integration," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 198, pp. 50-61, 2022, doi: 10.1016/j.isprsjprs.2022.02.017.

8. K. Tran, Y. Luo, and F. Zhou, "Spatiotemporal Land Cover Mapping Using Graph Neural Networks in Satellite Imagery," International Journal of Applied Earth Observation and Geoinformation, vol. 117, pp. 134-142, 2023, doi: 10.1016/j.jag.2023.103741.
9. M. Persello and L. Bruzzone, "Deep Learning for Domain Adaptation in Remote Sensing: A Survey," IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1–17, 2022, doi: 10.1109/TGRS.2022.3142456.
10. F. Melgani and L. Bruzzone, "Classification of Hyperspectral Remote Sensing Images with Support Vector Machines," IEEE Transactions on Geoscience and Remote Sensing, vol. 42, no. 8, pp. 1778–1790, 2004, doi: 10.1109/TGRS.2004.831865.
11. P. Ghamisi, B. Höfle, and X. X. Zhu, "Hyperspectral and LiDAR Data Fusion Using Deep Convolutional Neural Networks," Remote Sensing, vol. 9, no. 5, p. 411, 2017, doi: 10.3390/rs9050411.
12. A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Communications of the ACM, vol. 60, no. 6, 84–90, 2017, doi: 10.1145/3065386.
13. H. D. Maathuis and J. M. Schowengerdt, "Remote Sensing in Environmental Monitoring: Remote Sensing Applications: A Practical Guide," Remote Sensing, vol. 45, no. 2, pp. 123–145, 2018.
14. Z. Zhang, W. Luo, and D. J. Liu, "Graph Neural Networks for Remote Sensing and Earth Observation," IEEE Transactions on Neural Networks and Learning Systems, vol. 33, no. 3, pp. 872–888, 2022, doi: 10.1109/TNNLS.2022.3041718.