Geosight: Deep Learning–Based Satellite Image Analysis for Automated Disaster and Environmental Monitoring

M. Srividyareddy[1], M. Sai Praneeth Reddy[2], P. Ruthika Reddy[3], S. Sanjana[4]
[1]*Assistant Professor, Dept of Information Technology, Matrusri Engineering College, Hyderabad, India*
[2,3,4]*Student, Matrusri Engineering College, Hyderabad, India*

***Abstract*—Recent advances in remote sensing and deep learning have made it possible to analyze satellite imagery more efficiently for disaster assessment and environmental monitoring. This paper presents GeoSight, a framework designed to identify disaster-affected regions and analyze environmental changes using satellite images. The system combines convolutional neural network architectures such as U-Net and DeepLabV3+ with spectral indices including the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI). These techniques enable pixel-level segmentation of satellite imagery and help detect structural damage, vegetation variation, and water bodies.**

To estimate disaster impact, GeoSight compares satellite images captured before and after an event. The resulting analysis highlights affected areas and generates damage masks together with environmental statistics. By automating satellite image interpretation, the proposed system reduces the need for manual field surveys and traditional GIS workflows. Overall, GeoSight provides a practical and scalable approach for supporting disaster management and environmental monitoring using satellite-based observations.

***Index Terms*—Deep Learning, Disaster Damage Detection, NDVI, NDWI, Remote Sensing, Satellite Image Analysis.**

I. INTRODUCTION

Disaster management and environmental monitoring have traditionally relied on manual field surveys, expert interpretation, and Geographic Information System (GIS)–based workflows. Although these approaches provide valuable insights, they are often time-consuming and difficult to apply during large-scale disasters where rapid response is required. As a result, researchers have increasingly explored automated techniques for analyzing satellite imagery.

Recent advances in deep learning have significantly improved the ability to interpret satellite images. Convolutional Neural Networks (CNNs) and related segmentation models can identify patterns, detect structural damage, and extract useful information from high-resolution imagery. These techniques make it possible to compare satellite images captured at different time periods and quickly identify damaged infrastructure, vegetation loss, or changes in water bodies.

To address these challenges, this study proposes GeoSight, an automated satellite image analysis framework for disaster damage assessment and environmental monitoring. The system integrates deep learning–based segmentation models with change detection techniques and spectral indices such as NDVI and NDWI. By combining these components within a single framework, GeoSight enables rapid geospatial analysis and provides useful insights for disaster response and environmental monitoring.

II. LITERATURE SURVEY

Research on disaster assessment using satellite imagery has increasingly focused on deep learning models for segmentation and change detection. Deng and Wang [1] developed an improved U-Net architecture for identifying damaged buildings in post-disaster imagery, demonstrating improved segmentation accuracy for structural damage assessment.

Long et al. [2] introduced Fully Convolutional Networks (FCNs), which allow convolutional neural networks to perform pixel-level segmentation rather than simple image classification. This approach

enabled dense prediction tasks such as object segmentation in large images.
The well-known U-Net architecture proposed by Ronneberger et al. [3] improved segmentation accuracy by combining encoder–decoder structures with skip connections. Because of its ability to preserve spatial details, the model has been widely used in medical imaging and remote sensing analysis.

Chen et al. [4] proposed DeepLabV3+, a semantic segmentation model that uses atrous convolution and atrous spatial pyramid pooling to capture multi-scale contextual information. This approach significantly improves boundary detection and segmentation accuracy in complex scenes.
Large-scale datasets also play an important role in disaster damage analysis. Gupta et al. [5] introduced the xBD dataset, which contains paired pre- and post-disaster satellite images covering different disaster events. The dataset has become a benchmark for evaluating disaster damage detection algorithms.
Change detection techniques have also been widely explored in remote sensing. Ghosh et al. [6] reviewed deep learning approaches for identifying differences between satellite images captured at different time periods, highlighting the importance of convolutional and Siamese architectures for temporal analysis.
In addition to deep learning models, spectral indices are commonly used for environmental monitoring. Rouse et al. [7] introduced the Normalized Difference Vegetation Index (NDVI), which measures vegetation health using red and near-infrared spectral reflectance. Similarly, McFeeters [8] proposed the Normalized Difference Water Index (NDWI) to improve the detection of open water bodies in satellite imagery by enhancing spectral contrast between water and surrounding land surfaces.

Badrinarayanan et al. [9] proposed the SegNet architecture for semantic image segmentation. The model follows an encoder–decoder design and has been widely used in scene understanding and remote sensing analysis.

Zhu et al. [10] reviewed deep learning techniques used in remote sensing image analysis. Their study highlights the effectiveness of convolutional neural networks for land-cover classification and change detection.

Ji et al. [11] applied fully convolutional networks for segmenting multisource remote sensing images. Their work demonstrated improved extraction of spatial information from high-resolution satellite data.
Zhang et al. [12] explored deep learning methods for change detection in multi-temporal satellite imagery. Their research showed that neural networks can effectively identify structural and environmental variations.

Liu et al. [13] developed a deep learning approach for building damage detection using satellite images captured after disaster events. The model helps identify damaged infrastructure quickly.

Volpi and Tuia [14] studied deep multi-task learning for remote sensing image analysis. Their framework allows a single model to perform tasks such as classification and segmentation simultaneously.

Chen et al. [15] investigated deep learning-based change detection techniques for high-resolution satellite imagery. Their work demonstrated improved detection of temporal changes in geospatial data.

III. METHODOLOGY

GeoSight performs disaster damage detection along with vegetation and water percentage analysis using satellite images. The methodology comprises sequentially ordered steps, as illustrated in the architecture:

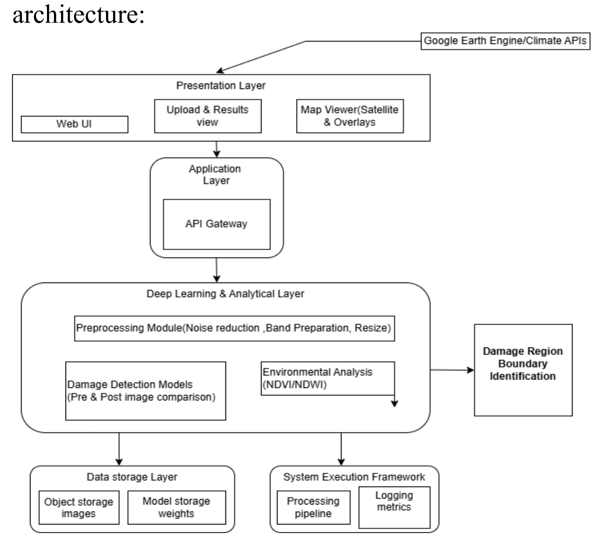

Fig. 1: System Architecture

A. Input Image Acquisition (Presentation and Application Layer)

Satellite images are uploaded through the web interface of the system. Users can provide either a single satellite image for environmental analysis or paired pre- and post-disaster images for damage assessment. The uploaded images are routed to the analytical pipeline, where they are stored and prepared for further processing.

B. Image Preprocessing Pipeline (Deep Learning and Analytical Layer)

Satellite images require preprocessing before analysis. In this stage, images are resized to a fixed resolution (512 × 512 pixels), noise is reduced, and spectral information is prepared for NDVI and NDWI computation. The images are then converted into numerical arrays so that they can be processed by the deep learning models. These steps ensure that images with different resolutions or lighting conditions can be analyzed in a consistent manner.

C. Damage Detection Models

The system uses convolutional neural network segmentation models such as U-Net and DeepLabV3+ to detect disaster-affected regions in satellite images. These models perform pixel-level classification and generate damage masks that highlight collapsed buildings, flooded land, or burned regions. The generated masks allow the system to identify affected areas and estimate the extent of damage.

D. Change Detection Model

To analyse disaster impact, pre- and post-event images of the same region are compared. Differences between the two images are used to detect newly damaged structures and environmental changes caused by the disaster.

E. Vegetation and Water Models

Vegetation and water coverage are estimated using spectral indices derived from satellite imagery. The Normalized Difference Vegetation Index (NDVI) is used to evaluate vegetation density, while the Normalized Difference Water Index (NDWI) helps identify water bodies within the observed region.

- NDVI = (NIR − Red) / (NIR + Red)
- NDWI = (Green − NIR) / (Green + NIR)

F. Damage Region Boundary Identification

After segmentation, the detected damage regions are highlighted by identifying connected pixel regions within the binary mask. These regions help visually represent the spatial extent of affected areas.

G. Data Storage and Processing Management

The system stores raw and processed images for further analysis and comparison. Model weights and configurations are maintained to ensure consistent evaluation during experimentation. This provides reproducibility and scalability for all disasters.

H. System Execution Framework

The framework supports sequential processing of uploaded satellite images, logging intermediate outputs, and tracking performance metrics during evaluation. The design of this layer enables reliable deployment and robust systems.

IV. DATASET

The xBD dataset was used as the primary dataset for this research. It contains paired pre- and post-disaster satellite images from multiple disaster events. These image pairs represent the same geographic region captured at different time periods, enabling temporal analysis of disaster damage. Additional publicly available satellite imagery was used for environmental index calculations.

V. OUTPUT VISUALIZATION

The output visualization phase presents damage detection results in a clear and interpretable format. The system provides visual summaries and analytical reports that highlight key findings based on user interaction.

Fig. 2: Pre-disaster satellite image

Fig. 2 presents the pre-disaster satellite image of a residential region prior to the Mexico earthquake event. It contains dense housing clusters, road networks and commercial structures.

Fig. 3

Presents the post-disaster satellite image of the same region following the earthquake. Structural variations and surface inconsistencies are observable across multiple regions.

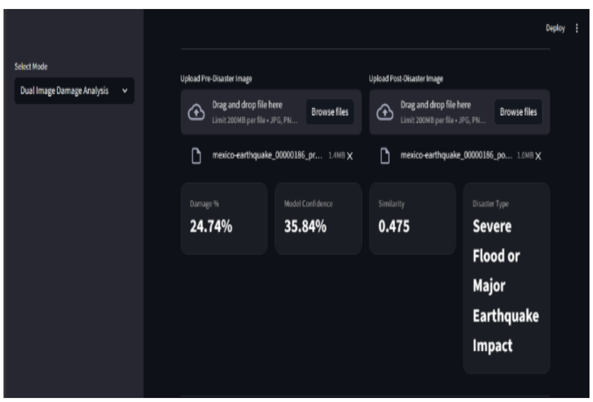

Fig. 4:Metrics

The developed system provides an interactive interface for dual-image disaster damage analysis using pre- and post-event satellite imagery. The model computes quantitative metrics including damage percentage, model confidence score, image similarity, and predicted disaster category. These metrics help in assessing the severity and reliability of detected changes.

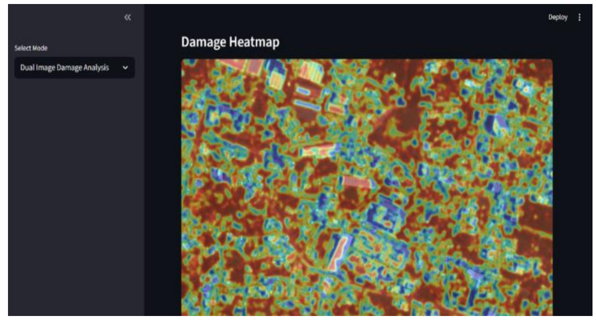

Fig. 5: Damage Heatmap

The damage heatmap visualizes the spatial distribution and intensity of detected changes between pre- and post-disaster images. High-intensity regions (red/yellow) indicate areas with significant structural variation, while cooler colors represent minimal change. This visualization helps identify severely affected zones quickly. It enhances interpretability by converting model outputs into an intuitive spatial representation.

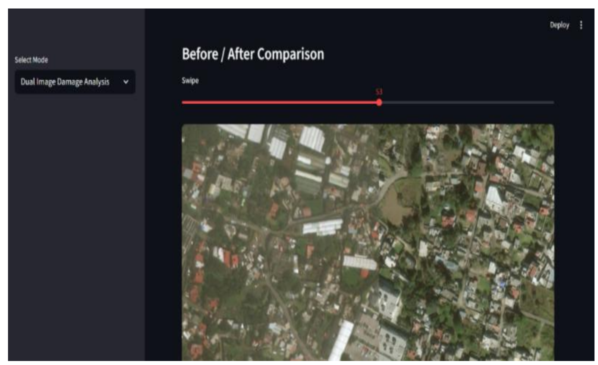

Fig. 6:Comparison between pre- and post-disaster

The swipe-based comparison tool allows interactive visualization of pre- and post-disaster satellite images. By sliding across the image, users can easily observe structural and environmental changes between the two time periods.

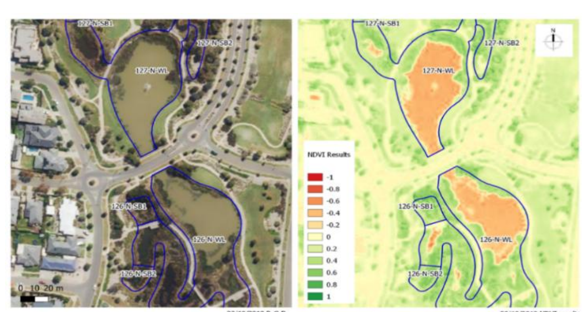

Fig. 7: NDVI Output

Fig. 7 shows the NDVI map generated from the satellite imagery. Vegetation density is represented using a colour gradient, where green indicates dense vegetation and red represents sparse or non-vegetated areas.

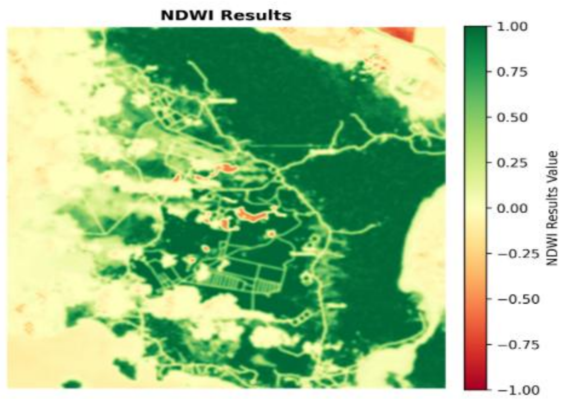

Fig. 8: NDWI Output

Fig. 8 presents the NDWI visualization derived from the satellite imagery. Higher NDWI values correspond to water regions, while lower values indicate land surfaces such as vegetation, soil, or built-up areas.

VI. CONCLUSION

GeoSight presents a practical framework that combines deep learning with satellite remote sensing for disaster assessment and environmental monitoring. By integrating segmentation models such as U-Net and DeepLabV3+ with change detection techniques and spectral indices including NDVI and NDWI, the system can identify damaged regions and analyze environmental changes from satellite imagery. This approach reduces reliance on manual surveys and traditional GIS-based workflows by automating image interpretation and statistical analysis.

The implementation demonstrates the ability to detect disaster damage at the pixel level and generate useful metrics for assessing affected regions. Temporal comparison of pre- and post-disaster images improves the reliability of change detection, while vegetation and water analysis extend the system's use beyond disaster response to environmental monitoring. Future improvements may include the use of transformer-based models and real-time satellite data integration to further enhance accuracy and scalability.

REFERENCES

[1] L. Deng and Y. Wang, "Post-disaster building damage assessment based on improved U-Net," Journal of Applied Remote Sensing, vol. 16, no. 3, pp. 036504-1–036504-16, 2022.

[2] J. Long, E. Shelhamer, and T. Darrell, "Fully Convolutional Networks for Semantic Segmentation," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3431–3440, 2015.

[3] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, pp. 234–241, 2015.

[4] L.-C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam, "Encoder–Decoder with Atrous Separable Convolution for Semantic Image Segmentation," *European Conference on Computer Vision (ECCV)*, pp. 801–818, 2018.

[5] R. Gupta, R. Hosfelt, S. Sajeev, et al., "xBD: A Dataset for Assessing Building Damage from Satellite Imagery," *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, pp. 10–17, 2019.

[6] A. Ghosh, S. Roy, and D. Bhattacharya, "Deep Learning for Change Detection in Remote Sensing Images: A Review," *IEEE Geoscience and Remote Sensing Magazine*, vol. 8, no. 2, pp. 84–100, 2020.

[7] J. W. Rouse, R. H. Haas, J. A. Schell, and D. W. Deering, "Monitoring Vegetation Systems in the Great Plains with ERTS," *NASA Special Publication*, 1974.

[8] S. K. McFeeters, "The Use of the Normalized Difference Water Index (NDWI) in the Delineation of Open Water Features," *International Journal of Remote Sensing*, vol. 17, no. 7, pp. 1425–1432, 1996.

[9] V. Badrinarayanan, A. Kendall, and R. Cipolla, "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 12, pp. 2481–2495, 2017.

[10] X. X. Zhu, D. Tuia, L. Mou, G. S. Xia, L. Zhang, F. Xu, and F. Fraundorfer, "Deep Learning in Remote Sensing: A Comprehensive Review,"

IEEE Geoscience and Remote Sensing Magazine, vol. 5, no. 4, pp. 8–36, 2017.

[11] S. Ji, S. Wei, and M. Lu, "Fully Convolutional Networks for Multisource Remote Sensing Image Segmentation," IEEE Transactions on Geoscience and Remote Sensing, vol. 56, no. 4, pp. 2304–2318, 2018.

[12] Y. Zhang, L. Zhang, and B. Du, "Deep Learning for Remote Sensing Image Change Detection," IEEE Access, vol. 7, pp. 85813–85826, 2019.

[13] Y. Liu, C. Wu, and Y. Liu, "Building Damage Detection Using Convolutional Neural Networks and Satellite Imagery," Remote Sensing, vol. 12, no. 19, 2020.

[14] M. Volpi and D. Tuia, "Deep Multi-Task Learning for Remote Sensing Image Analysis," IEEE Transactions on Geoscience and Remote Sensing, vol. 56, no. 8, pp. 4789–4802, 2018.

[15] H. Chen, C. Zhang, and X. Li, "Deep Learning-Based Change Detection for High-Resolution Satellite Imagery," Remote Sensing Letters, vol. 12, no. 6, pp. 589–598, 2021.