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Object Detection in Satellite Images using Deep learning

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Abstract - Object detection and change detection in satellite imagery play a key role in environmental monitoring, urban planning, and disaster response. This project uses deep learning techniques to enhance accuracy in identifying changes over time. Initially, K-means clustering and kernel-based methods were used for image segmentation. Later, a Siamese Neural Network (SNN) was implemented to compare satellite image pairs and detect structural differences effectively.

To improve detection, a Siamese Attention U-Net (SNN-AUNet) was introduced, which uses attention mechanisms to capture fine spatial and contextual details. This approach handles challenges like noise, scale variation, and complex structures, providing accurate insights into land cover and infrastructure modifications. The system supports better decision-making across domains like agriculture, urban development, and disaster management.

***Key Words*: Satellite Imagery, Change Detection, Siamese Neural Network, Attention Mechanism, Deep Learning**

1.INTRODUCTION

Satellite image analysis stands as a vital component in understanding Earth's dynamic surface, offering deep insights into land cover changes, infrastructure growth, and environmental transformations. The use of satellite imagery has proven indispensable in domains such as urban planning, agriculture, and disaster response, enabling timely decisions through large-scale visual data. This project aims to explore the potential of deep learning for object detection in satellite images, focusing on identifying meaningful changes over time.

The traditional methods used for image segmentation and feature extraction, such as K-means clustering and kernel-based techniques, offer foundational insight but often fall short when addressing scale variation, image noise, and structural complexity. To overcome these limitations, the system integrates an advanced Siamese Attention U-Net (SNN-AUnet), leveraging attention mechanisms to capture fine-grained spatial features and context. A custom dataset comprising 1,000 image pairs from Google Earth Engine was curated, ensuring variety across urban, agricultural, and infrastructural landscapes.

By adopting this approach, the system not only enhances accuracy but also contributes to scalable, automated change detection. The attention-driven model ensures improved interpretability and adaptability across different geospatial contexts, positioning this project as a meaningful contribution to sustainable development and real-time environmental monitoring.

1.1 OBJECTIVE

The primary aim of this project is to develop an intelligent system capable of automatically detecting changes in satellite images using deep learning techniques. This system is designed to compare satellite images captured at different time intervals and accurately identify regions where significant transformations have occurred. These changes may include urban development, environmental alterations, or damage resulting from natural disasters. To fulfill this goal, the project employs advanced neural network models—specifically, Siamese Neural Networks (SNN) and Siamese Attention U-Net—that are well-suited for analyzing paired satellite images. These models are structured to extract and compare deep features from two input images, enabling the detection of subtle and complex changes with high precision. The integration of attention mechanisms enhances the system's ability to focus on relevant spatial features while minimizing noise and irrelevant data.

The core objectives of the project include designing a robust framework that applies deep learning to detect visual differences between multi-temporal satellite images, enhancing the model's accuracy through attention-based feature refinement, reducing false detections via deep contextual analysis, and building a scalable solution that operates efficiently on large datasets without manual intervention. By automating the change detection process, this project contributes to critical applications in areas such as urban planning, environmental monitoring, and disaster management. Ultimately, the system aims to provide decision-makers with timely, accurate, and actionable insights derived from satellite imagery, enabling more informed and effective responses to dynamic real-world changes.

1.2 METHODOLOGY

This project utilizes a deep learning-based framework to automatically detect and analyze changes in satellite imagery captured at different time intervals. The core methodology involves comparing two temporally distinct satellite images to identify areas where significant transformations have occurred. These changes may include urban expansion, deforestation, environmental shifts, or damage caused by natural disasters. To achieve this, a comprehensive pipeline is implemented, combining Siamese Neural Networks (SNN) and Siamese Attention U-Net architectures—both designed to process paired satellite images and detect fine-grained pixel-level differences

The process begins with data collection and preprocessing, where a set of satellite image pairs is gathered and spatially aligned to ensure consistency. Preprocessing techniques such as resizing, normalization, image augmentation (e.g., flipping or rotation), and patch generation are applied to prepare the dataset for training. The methodology involves deploying two distinct deep learning architectures for comparison: the first is a Siamese Neural Network comprising two identicalconvolutional branches that independently process the image pair while sharing weights, allowing feature comparison; the second is Siamese Attention U-Net, which builds upon the basic Siamese framework by incorporating an encoder-decoder structure enhanced with attention mechanisms to focus on the most relevant spatial features, thereby improving detection accuracy.

Once the data is preprocessed and the models are selected, the training phase begins. Both models are trained using labeled image pairs and their corresponding binary change maps, which indicate regions of change and no change. Loss functions such as Binary Cross Entropy and Dice Loss are used to reduce prediction errors, while optimization is achieved through techniques like the Adam optimizer and learning rate schedulers. During the change detection stage, the aligned satellite images are input into the trained model, where feature maps are extracted and compared to generate either binary or probabilistic change maps highlighting modified regions. Model performance is then evaluated using metrics such as accuracy, precision, recall, F1-score, and Intersection over Union (IoU) to assess the correctness and completeness of the detected changes.

Finally, the results are visualized using binary masks or color overlays on the original images to clearly represent the areas of change. These visual outputs can be applied in practical scenarios such as environmental monitoring, infrastructure planning, or disaster damage assessment, making the system valuable for real-world decision-making and geospatial analysis.

1.3 DATASET CHARACTERISTICS

The dataset used in this project comprises high-resolution satellite images captured across different years, allowing for effective detection of temporal changes in selected regions of Goa. The images offer excellent spatial resolution, enabling detailed observation of both natural and man-made transformations in the landscape. To further enhance the analysis, multi-spectral data including Red, Green, Blue (RGB), and Near-Infrared (NIR) bands were utilized. These spectral bands are crucial in identifying and highlighting changes related to urban development, vegetation cover, and water bodies.

The region of interest primarily focuses on areas in Goa that are undergoing significant infrastructure and environmental changes. Notable locations include the Manohar Parrikar Atal Setu (bridge over the Mandovi River), the New Zuari Bridge, and the Mopa International Airport (Manohar International Airport). The dataset also covers the South Goa District Hospital redevelopment (Hospicio), the GMC Cancer Block at Goa Medical College in Bambolim, various road expansion sites, newly constructed temples and religious structures, as well as regions experiencing deforestation and the transformation of agricultural land. These carefully selected areas offer a diverse and relevant sample set for training and evaluating the deep learning models for change detection.

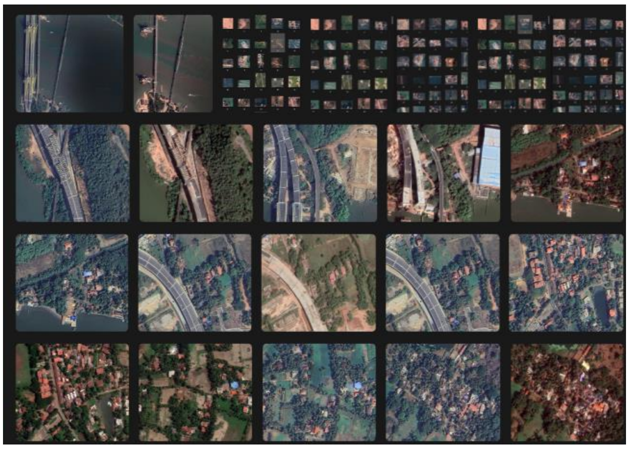

Fig -1: Dataset Generated

Table -1: Key Challenges in generating dataset

Challenge	Resolution
Manual Snapshotting	Images captured manually from GEE for specific sectors not available as pre-packaged datasets.
Cloud and Shadow Noise	Handled using GEE's cloud masking before export and morphological filters after model prediction.

Image Alignment	Spatial consistency ensured in GEE before capturing paired images.
Data Imbalance	Augmentation techniques like flipping and rotation applied on minority samples.
Computational Load	PCA and patching strategy used to reduce memory and time complexity.

2. RESULTS AND DISCUSSION

The proposed system for Satellite Image Change Detection using Siamese Attention U-Net (SNN

AUNet) was evaluated using a custom-created dataset consisting of 1,000 image pairs, collected

via Google Earth Engine. Each pair consists of a "before" and "after" image of the same geographic

region—capturing sectors such as agriculture, infrastructure, and urban development.

The objective of this phase was to evaluate the model's capability to detect meaningful changes

between satellite image pairs and represent them through clearly visualized outputs.

Fig -2: Input Image pairs

This model provides a scalable and efficient solution for geospatial change monitoring. When applied to diverse domains such as urban planning, agriculture, disaster management, or deforestation tracking, the insights generated can serve as critical decision-making tools.

Unlike traditional image comparison methods, the Siamese Attention U-Net enhances context-aware learning by comparing deep feature embeddings, making it robust against minor variations like brightness, shadows, or seasonal color changes.

The performance of various change detection methods was evaluated based on model type, accuracy, and visual results. Among the classical unsupervised techniques, K-Means Clustering offered a fast and straightforward approach for identifying major changes but lacked the precision needed for finer analysis. The combination of PCA and Morphological Operations helped emphasize large-scale transformations but failed to capture subtle changes effectively.

On the other hand, Siamese Neural Network (SNN), a supervised deep learning model, showed a significant improvement in accuracy (~80%) for binary change detection tasks. However, it was limited by its inability to provide detailed pixel-level outputs.

The most advanced model, Siamese Attention U-Net (SNN-AUNet), demonstrated the highest visual accuracy and was capable of generating precise change maps with fine-grained spatial detail. Its attention mechanism allowed the network to focus on critical regions, making it the most reliable choice for satellite image change detection in this study.

Table -2: Comparison of Change Detection Methods

Method	Model Type	Accuracy / Performance	Remarks
K-Means Clustering	Unsupervised (Classical)	Moderate (Visual Only)	Simple and fast, but lacks fine precision
PCA + Morph Ops	Unsupervised (Classical)	Low to Moderate	Highlights patterns but misses small changes
SNN	Supervised (Deep Learning)	~80% on test data	Good binary detection, lacks pixel detail
SNN-AUNet	Supervised (Deep Learning)	High accuracy (visually precise)	Best performance; accurate pixel-level output

3. CONCLUSIONS

The proposed Satellite Image Change Detection system using Siamese Attention U-Net (SNN-AUNet) has demonstrated a high level of accuracy and reliability in identifying meaningful differences between satellite image pairs. The system effectively processed and analyzed 1,000 image pairs across various sectors, including agriculture, infrastructure, and urban development.

By leveraging the power of deep learning, specifically Siamese architecture and feature similarity analysis, the model was able to detect even subtle changes in land cover and structures. The integration of image preprocessing, L2 distance-based similarity calculation, and postprocessing using morphological techniques helped enhance the accuracy and clarity of the detected changes.

The generated Difference Maps, Change Maps, and Morphological Output Maps have been visually consistent with actual observable differences, indicating that the system is well-suited for practical applications in areas such as:

Disaster management (e.g., flood or landslide impact analysis)

Urban planning (e.g., monitoring of construction or land-use transformation)

Agricultural surveillance (e.g., crop monitoring, land usage changes)

The system also produced a quantitative similarity score, offering a numerical interpretation of image similarity, which can be valuable for automated reporting and integration into larger geospatial systems

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