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Unsupervised Change Detection in Satellite Images using Deep Learning

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***Abstract*— Change detection in satellite image time series is a crucial task for urban growth, environmental change, disaster effects, and land use studies. However, the process of acquiring labelled ground truth data for supervised learning methods is costly, time-consuming, and infeasible for large-scale remote sensing problems. To overcome this shortcoming, this paper presents a novel fully unsupervised deep learning architecture for change detection in a series of multispectral satellite images.**

The proposed architecture uses a convolutional autoencoder that is trained on a sequence of multi-band satellite images capturing the normal state of a given scene. Each image has 13 spectral bands from the Sentinel-2 satellite image data, allowing for a detailed spatial-spectral characterization. The autoencoder discovers the patterns of unchanged areas without any supervised learning.

To enhance the interpretability of the proposed architecture, K-Means clustering is used on the change maps to classify the identified areas into distinct change intensity classes. The proposed architecture is simple, efficient, and free from temporal consistency and supervised learning. The experimental results on multi-temporal satellite image data show that the proposed architecture successfully identifies significant structural and environmental changes with minimal reliance on labelled data.

I. INTRODUCTION

Satellite images taken over time open up a lot of possibilities. You can track how cities grow, keep tabs on the environment, assess damage after disasters, or figure out how land is being used. Now that we’ve got easy access to multispectral data from satellites like Sentinel-2, the options are even broader. Traditional change detection methods rely on pixel differencing, statistical models [1], [2], or hand-crafted features, which are often sensitive to noise, illumination variations, and atmospheric conditions.

Supervised deep learning approaches have shown improved performance [3], [4], [5] but require large amounts of labelled data, which is difficult to obtain for satellite imagery. To overcome these limitations[6], this work proposes an unsupervised change detection framework based on autoencoder neural networks. Unlike existing approaches that focus on single image pairs, the proposed method leverages a series of satellite images with 13 spectral bands, enabling robust detection of temporal changes. The method is simple, scalable, and does not depend on labelled ground truth data.

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II. LITERATURE REVIEW

Satellite image change detection plays a vital role in many real-world applications such as urban development monitoring, deforestation analysis, disaster assessment, agricultural analysis, and environmental monitoring.

A. Traditional Change Detection Methods

Early change detection techniques mainly relied on traditional image processing and statistical methods—like image differencing, image ratioing, change vector analysis (CVA), principal component analysis (PCA), and independent component analysis (ICA)—have been around for a while. PCA and ICA try to shrink the data down and make changes stand out, but when you use them on complex, high-res satellite images, they usually struggle. Accuracy drops, and they just aren't that reliable.

B. Supervised Deep Learning Methods

Deep learning has really changed the game for change detection. These days, supervised convolutional neural networks (CNNs) are everywhere. People use models like fully convolutional networks (FCNs), U-Net, and Siamese networks to pull out the important details from pairs of images taken at different times. Siamese networks stand out—they run both images through the same network with shared weights, then compare what they find to spot any changes.

C. Unsupervised and Semi-Supervised Methods

To overcome the dependency on labelled data, researchers have explored unsupervised and semi-supervised approaches. Autoencoders (AEs) have been widely used for unsupervised feature learning and anomaly detection[6], [9]. In such approaches, the autoencoder is trained to reconstruct normal image patterns, and areas with high reconstruction error are considered as changed or anomalous regions. Kalinichevaetal. proposed an unsupervised framework that combines autoencoders with graph-based temporal modelling and GRU networks[7], [8], [10], [11] to detect and cluster change processes in satellite image time series.

III. METHODOLOGY

In this work, we present an unsupervised deep learning framework for spotting changes in satellite image time series (SITS). Unlike traditional supervised approaches, the proposed method does not require labeled change maps and is designed to work with multi-temporal, multi-spectral satellite data. The approach focuses on distinguishing unchanged regions from changed regions such as new constructions, infrastructure development, vegetation loss, land-use modification.
The proposed framework consists of the following main stages.

$$RS = \{I_1, I_2, \ldots, I_S\}$$

be a time series of coregistered satellite images, where each image contains 13 spectral bands. The proposed framework is illustrated in figure 1

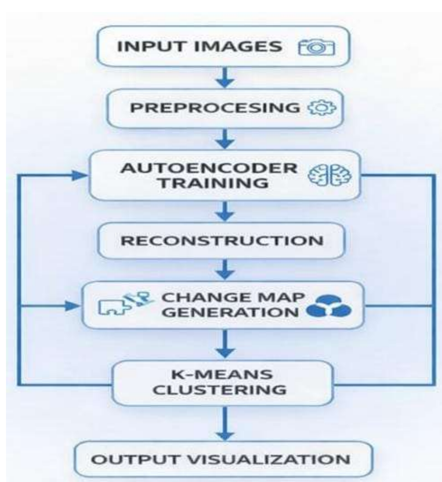

Fig 1: Proposed Framework

A. Input Image Series Preparation

A sequence of satellite images is divided into before-series images and after-series images. Each image contains multiple spectral bands, allowing the model to capture rich spatial and spectral information.

B. Preprocessing

All input images are preprocessed to ensure consistency:
- Selection of relevant spectral bands (RGB extracted from 13 bands)
- Image resizing to a fixed resolution
- Normalization of pixel values to the range [0, 1]

$$I_{norm} = \frac{(I - I_{min})}{(I_{\max - I_{min}})}$$

A convolutional autoencoder is trained using the before-image series only. The autoencoder learns a compact representation of unchanged regions by minimizing the reconstruction error between the original image and the reconstructed output.

$$Loss = \left(\frac{1}{N}\right)\sum_{i=1}^{N}(x_i - \{x\}_i)^2$$

C. Reconstruction-Based Change Detection

The trained autoencoder is then applied to the after-image.
For each image the autoencoder reconstructs the image.

D. Change Map Generation

The reconstruction error map is processed using thresholding techniques to generate a binary change map, separating:
- Changed regions
- Unchanged regions

This step converts reconstruction errors into spatial change information.

$$T = \arg\min_{\tau}\left[\sigma^2{}_{within(\tau)}\right]$$

IV. Data and Data Preprocessing

In this work, we evaluate the proposed unsupervised change detection framework using multi-temporal multispectral satellite image seriesfrom the Sentinel-2 earth observation mission. Sentinel-2 provides high-resolution optical imagery suitable for monitoring urban development, land-use changes, and environmental variations[12-16].
The dataset used in this project consists of time-series satellite images captured over the same geographical region at different timestamps. For each location, two temporal image stacks are considered:
- Before image series (T_1): A set of multispectral images representing the scene before changes occurred
- After image series (T_2): A corresponding set of multispectral images captured after changes

Each temporal stack contains 13 spectral bands, corresponding to Sentinel-2 multispectral channels, including visible, near-infrared, and short-wave infrared bands. These bands will capture complementary spectral information, enabling improved detection of structural and surface-level changes.
Here are the 13 spectral bands:
- Coastal aerosol
- Blue
- Green
- Red
- Several vegetation red edge bands
- Near Infrared (NIR)
- Narrow NIR
- Short-Wave Infrared (SWIR)

These multi-band inputs allow the model to detect subtle changes that may not be visible in RGB imagery alone. Unlike traditional bitemporal approaches that rely on only two images, the proposed framework processes a series of images at each timestamp[17-21]. The autoencoder learns a representation of normal spatiotemporal patterns from the before image series and detects deviations when reconstructing the after image series. Table 1 shows the characteristics of dataset

TABLE I: DATASET CHARACTERISTICS SUMMARY

Property	Description
Satellite	Sentinel-2 [12]
Data Type	Multispectral Optical Images
Number of Bands	13
Temporal Setup	Image Series (Before & After)
Spatial Resolution	Up to 10 m
Labels Required	No (Unsupervised)
Ground Truth Usage	Only for evaluation

V. EXPERIMENTS AND RESULTS

This section describes the experimental setup, parameter configuration, and results obtained from the proposed unsupervised satellite image change the detection framework. The main objective of the experiments is, to validate the effectiveness of the auto encoder-based approach in detecting real land-cover changes from satellite images taken at different times without using labelled training data. Table 2 shows the hyperparameters

TABLE II: HYPERPARAMETERS

Parameter	Value	Reason
Image Size	128×128	Speed–accuracy balance
Epochs	50	Proper convergence
Learning Rate	0.001	Stable training
Clusters (k)	3	Meaningful segmentation
Bands Used	13 bands (RGB extracted)	Rich spectral information

The experiments are performed on a machine with an Intel Core processor, sufficient RAM, and GPU support for faster neural network training. The deep learning models were implemented using Python and TensorFlow / PyTorch, and image processing operations were carried out using standard scientific libraries such as NumPy and OpenCV.For experimental evaluation, multi-temporal satellite images acquired from open-source Earth observation missions such as Sentinel-2 (and/or Landsat, if applicable to your project) were used.
Before applying the change detection algorithm, several preprocessing steps were performed to ensure data consistency and improve model performance:

A. Image Registration

All satellite images were aligned to a common coordinate system so that the same pixel location corresponds to the same ground location across time.

B. BandSelection

Spectral bands relevant for land-cover analysis (Red, Green, and NIR) were selected, as they effectively capture vegetation and urban changes.

C. Normalization

Pixel values are normalized to a common scale to reduce radiometric differences caused by illumination and sensor variations.

D. Patch Extraction

The images were divided into small fixed-size patches. Each patch represents a local spatial neighborhood and serves as an input sample for the autoencoder model.

Change Map Generation

For each pair of consecutive satellite images, a bitemporal change map is generated using the reconstruction error values.
To convert the continuous reconstruction error map into a binary change map:

- Otsu’s thresholding method[13] is applied automatically.
- Pixels with reconstruction error values above the threshold are marked as changed.

➢ Pixels below the threshold are considered unchanged.
This process produces a binary change map highlighting areas of potential land-cover change.

Evaluation Metrics
Since the approach is unsupervised, evaluation was performed [14] using manually interpreted reference regions for selected areas.
The following metrics are used:
Precision: It measures the proportion of correctly detected change pixels among detected change pixels.
Precision = TP / (TP + FP)
Recall: It measures the proportion of actual change pixels[14] which were successfully detected.
Recall = TP / (TP + FN)
Overall Accuracy: Indicates the general correctness of change detection results.
Accuracy = (TP + TN) / total
The executed results are shown below:

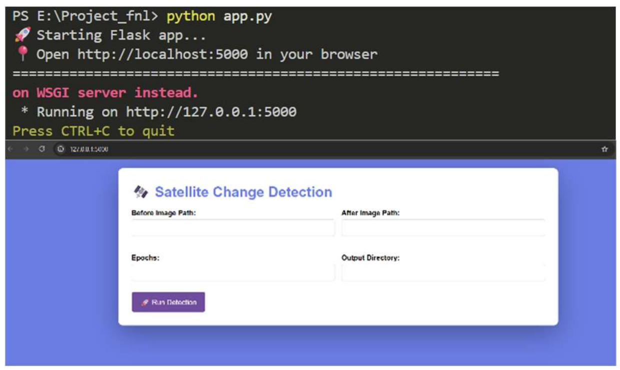

Fig 2

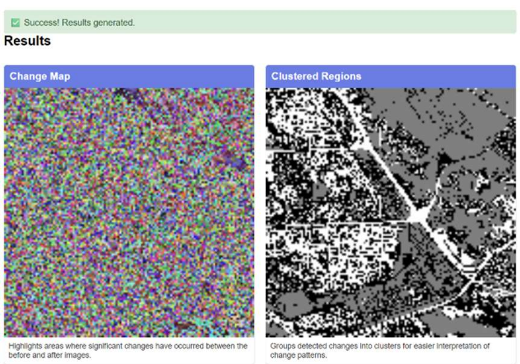

Fig 3

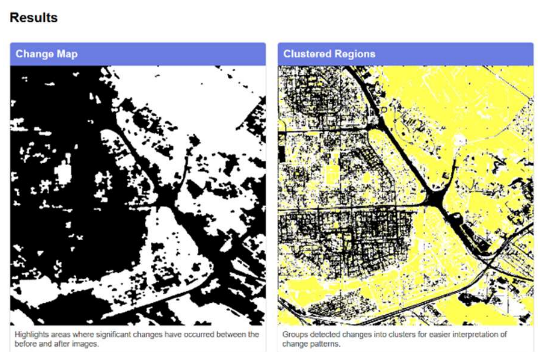

Fig 4

VI. OUTPUT VISUALIZATION

Finally, the system generates:
➢ Change intensity maps
➢ Clustered change maps
➢ Visual overlays on original images
These outputs help in understanding where changes occurred.
The models focus on reducing reconstruction loss with Mean Squared Error (MSE) [6].

$$MSE(o,t) = \left(\frac{1}{N}\right)\sum_{n=1}^{N}(o_n - t_n)^2$$

where o is the output patch, t is the target patch, and N is the number of patches. To convert the reconstruction error map into a binary change map, Otsu's automatic thresholding is applied [13].

The complete steps of the algorithm are:

- Pretrain the model using the entire SITS dataset.
- Fine-tune the joint AE model for each pair of images.
- Calculate the reconstruction error for every patch.
- Use Otsu thresholding to create a binary change map.
- Produce $S - 1$ change maps for the whole SITS dataset.

The convolutional AE and fully convolutional AE architectures for change detection come straight from the approach in.

VII. Conclusion

In this paper, we presented an unsupervised deep learning–based approach for detecting changes in the satellite image time series. The method relies on convolutional autoencoders to identify non-trivial changes by analysing reconstruction errors between consecutive satellite images.

The proposed framework does not require labelled training data and does not depend on regular temporal intervals, making it suitable for real-world satellite datasets. Experimental results demonstrate that the method can effectively detect meaningful land-cover changes while suppressing seasonal variations.

Overall, the project demonstrates the effectiveness of unsupervised deep learning techniques for the satellite images to change detection and provides a strong foundation for further research and real-world applications.

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