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Deep Learning-Based Change Detection In Satellite Images Using Channel-Spatial Differences And Layer-Exchange Mechanism

[1]P. Pavani,[2]Seeram Naga Venkata Navyambica,[3]Shaik Fathima Begum,[4]Penuboyina Santhosh Kumar,[5]Pragada Sai Teja Prasanna Kumar

[1]Assistant Professor, Department of CSE-Data Science, Eluru College of Engineering and Technology

[2,3,4,5]B. Tech Student, Department of CSE-Data Science, Eluru College of Engineering and Technology

ABSTRACT

Remote sensing change detection is a fundamental technique in Earth observation applications, including environmental monitoring, disaster assessment, and urban development analysis. The primary objective is to identify differences between two satellite images of the same geographic region captured at different time intervals. Conventional deep learning approaches mainly focus on spatial differences between images and often fail to capture subtle or gradual changes because they do not fully utilize feature channel information and temporal dependencies. This study proposes a deep learning–based change detection framework called LENet, which integrates a Channel–Spatial Difference Weighting (CSDW) module and a layer-exchange decoding structure. The framework processes bi-temporal satellite images using deep encoders to extract discriminative feature maps. The CSDW module computes difference information across both spatial and channel dimensions, enabling effective identification of structural and spectral variations, while the layer-exchange decoding mechanism strengthens interaction between temporal features and captures correlations between images from the same geographical area. Experimental evaluations conducted on benchmark datasets, including CLCD, PX-CLCD, LEVIR-CD, and S2Looking, demonstrate that the proposed model achieves a change detection accuracy of 97.8%, producing more precise pixel-level change maps compared to conventional CNN and Siamese architectures. The proposed system effectively detects subtle, gradual, and large-scale changes, making it suitable for practical applications such as deforestation monitoring, urban expansion analysis, and disaster damage assessment.

Keywords: Deep Learning, Satellite Image Analysis, Change Detection, Remote Sensing, Convolutional Neural Networks (CNN), Channel–Spatial Feature Difference, Layer Exchange Mechanism, Image Feature Extraction, Multi-Temporal Image Processing, Land Cover Monitoring.

I. INTRODUCTION

Change detection in remote sensing imagery is a fundamental task in Earth observation, aiming to identify differences between images captured at different times over the same geographic area. This capability is critical for applications such as urban development monitoring, environmental assessment, disaster management, and infrastructure planning. Accurate detection of changes at the pixel level enables better decision-making in urban planning, agriculture, and natural resource management. Traditional approaches to change detection rely on simple image differencing, thresholding, or manual interpretation, which are often limited in accuracy and scalability, especially when dealing with high-resolution or multi-temporal datasets.

With the rise of deep learning techniques, convolutional neural networks (CNNs) and encoder-decoder architectures have become the standard for remote sensing image change detection. Models such as Siamese networks leverage shared-weight encoders to extract spatial features from bitemporal images and detect changes by computing differences between feature maps. While these methods improve segmentation accuracy compared to conventional techniques, they primarily focus on spatial differences and often neglect the rich information present in the channel dimension of feature maps. Consequently, subtle spectral or semantic changes between temporal images can be missed, leading to false negatives or reduced detection accuracy in complex scenarios.

Recent research has explored attention mechanisms and transformer-based architectures to capture long-range dependencies and emphasize important spatial regions. Although these methods improve sensitivity to small-scale changes and global context modeling, they often treat spatial and channel information independently rather than jointly modeling the differences across both dimensions. Moreover, existing approaches rarely exploit the strong temporal and geographic correlations inherent in bitemporal images. Without mechanisms to explicitly interact and exchange information between the feature maps of two time points, the models are limited in their ability to detect gradual, minor, or complex changes.

To address these limitations, this study proposes a novel change detection framework, LENet, which integrates a Channel-Spatial Difference Weighting (CSDW) module and a Layer-Exchange decoding structure. The CSDW module computes differences across both spatial and channel dimensions, enabling the model to capture subtle, gradual, and large-scale changes effectively. The layer-exchange decoder facilitates inter-image feature interaction, allowing the network to leverage temporal dependencies and geographic alignment. By combining dual-dimensional difference learning with enhanced temporal correlation modeling, the proposed framework achieves superior feature discrimination and improves overall change detection performance.

Extensive experimental evaluation on benchmark datasets such as CLCD, PX-CLCD, LEVIR-CD, and S2Looking demonstrates that LENet outperforms conventional Siamese and encoder-decoder-based methods in terms of precision, recall, F1-score, and overall accuracy. The model proves robust in detecting subtle changes, handling complex real-world scenarios, and reducing false negatives. The proposed approach represents a significant advancement in intelligent remote sensing analysis, providing a reliable and efficient solution for multi-temporal change detection.

II. LITERATURE SURVEY

Fully Convolutional Siamese Networks for Change Detection

Author(s): Daudt, R. C., Le Saux, B., Boulch, A. (2018)

Abstract:

This study introduces Fully Convolutional Siamese Networks (FC-SN) for pixel-level change detection in remote sensing imagery. The method processes bitemporal images using shared-weight encoders and computes spatial differences between feature maps. FC-SN demonstrates improved segmentation accuracy over traditional image differencing techniques. However, it primarily focuses on spatial feature subtraction and does not consider channel-wise differences, limiting its ability to detect subtle spectral or semantic changes.

Attention-Based Change Detection Networks

Author(s): Peng, X., Li, R., Zhang, Y. (2019)

Abstract:

This research proposes the use of attention mechanisms, including spatial and channel attention modules, to enhance deep learning-based change detection. Attention networks focus on important regions and suppress irrelevant information, improving sensitivity to small object changes in high-resolution images. Despite this improvement, these methods typically model spatial and channel attention independently, failing to jointly capture difference information across both dimensions.

LEVIR-CD Dataset and Building Change Detection Methods

Author(s): Chen, H., Shi, Z., Zhu, K. (2020)

Abstract:

The study introduces the LEVIR-CD dataset, a large-scale benchmark for building change detection. Encoder-decoder and Siamese network architectures were evaluated on this dataset, showing promising results for large structural changes. However, many models struggle with minor or gradual changes, resulting in false negatives in complex urban areas due to insufficient temporal feature interaction between bitemporal images.

Multi-Scale Convolutional Neural Networks for Change Detection

Author(s): Zheng, Z., Zhong, Y., Ma, A., Zhang, L. (2020)

Abstract:

This work presents multi-scale CNN architectures for capturing changes at different resolutions. Hierarchical feature extraction at multiple scales improves detection performance for objects of varying sizes. Although multi-scale models enhance contextual understanding, they primarily rely on spatial differencing and underutilize channel-wise feature differences and temporal correlations.

Transformer-Based Change Detection Approaches

Author(s): Liu, J., Gong, M., Qin, A. (2020)

Abstract:

This research applies Transformer architectures to model long-range dependencies and global context in remote sensing change detection. Transformers enhance feature interaction between bitemporal images, achieving competitive accuracy. However, they require large datasets, high computational resources, and do not explicitly implement a unified mechanism to compute channel-spatial difference weighting.

Deep Supervised Change Detection Networks

Author(s): Shi, W., Zhang, Z., Zhang, X. (2022)

Abstract:

Deep supervised networks introduce auxiliary supervision at intermediate layers to improve gradient flow and feature

learning for change detection. These models achieve better convergence and improved F1-scores on benchmark datasets like CLCD and S2Looking. Nevertheless, they lack a dedicated mechanism for aggregating difference information across both spatial and channel dimensions, limiting their sensitivity to subtle or gradual changes.

Channel Attention and Spatial Attention-Based Deep Networks

Author(s): Zhang, Q., Yang, M., Zhang, Y. (2022)

Abstract:

This study incorporates channel attention and spatial attention mechanisms in a deep network for remote sensing change detection. The network enhances the focus on relevant change features while suppressing background noise. Despite improved performance, the approach treats spatial and channel attentions separately, without jointly modeling their difference information, which is crucial for capturing subtle bitemporal changes.

III. EXISTING SYSTEM

The current change detection systems utilized in remote sensing imagery are reliant on deep learning techniques utilizing pixel-level segmentation. These models typically determine the crack between bitemporal images, by extracting features along the spatial dimension only . More specifically, the change detection process identified two temporal images using conventional convolutional neural networks (CNNs), using some form of a Siamese network or an encoder-decoder. Although the above pipeline works to some extent, it does not harness all the multi- dimensional information provided in feature maps.

IV. PROPOSED SYSTEM

The proposed mechanism brings about a scope of differences in two important ways: through the channel-spatial difference weighting (CSDW) module and layer-exchange decoding structure within the LENet model thereby improving change detection accuracy. In particular, the CSDW module enables the model to compute differences spatially and across the channel dimension, which takes into consideration subtle changes in bitemporal images while improving sensitivity to change. The layer-exchange decoding structure facilitates further interaction of bitemporal features by allowing the model to consider their geographic and temporal correlations. Overall, these contributions enable the model to learn more discriminative difference features which, as highlighted, allows for very high levels of accuracy in change detection.

V. SYSTEM ARCHITECTURE

The system architecture for the proposed deep neural network–based satellite image change detection framework is designed to automatically identify changes between multi-temporal satellite images using channel–spatial feature differences and a layer-exchange mechanism. The architecture consists of several interconnected stages including data acquisition, preprocessing, feature extraction, feature difference computation, deep learning–based change detection, and result visualization.

Initially, the data acquisition module collects multi-temporal satellite images captured at different time periods for the same geographical location. These images are obtained from remote sensing platforms such as satellites or aerial imaging systems. The collected images may contain variations caused by urban development, environmental changes, deforestation, or natural disasters. Since satellite images often vary in resolution, illumination, and noise levels, a preprocessing stage is applied to improve data quality. This stage includes

image resizing, normalization, noise reduction, and spatial alignment to ensure that both images correspond to the same geographic coordinates.

After preprocessing, the images are passed to the feature extraction module, which utilizes a deep neural network, typically a Convolutional Neural Network (CNN), to learn hierarchical spatial features from the satellite images. The CNN extracts high-level semantic representations such as edges, textures, and structural patterns from each image. These deep features are then forwarded to the channel–spatial difference module, where differences between the feature maps of the two images are calculated across both channel and spatial dimensions. This process highlights areas where significant changes have occurred between the two time instances.

To further enhance feature interaction, a layer exchange mechanism is incorporated within the deep network architecture. In this stage, intermediate feature maps from different layers of the neural network are exchanged or fused to strengthen contextual understanding and improve detection accuracy. This mechanism enables the model to capture both low-level details and high-level semantic information, leading to more accurate identification of subtle changes in satellite imagery.

The resulting combined feature representations are then processed by the change detection module, where the deep learning model classifies pixels or regions as either changed or unchanged. The model outputs a change map that clearly highlights modified areas in the satellite images. Finally, the visualization and output module presents the detected changes in the form of a graphical change map, allowing users to easily interpret the results for applications such as urban monitoring, environmental assessment, and disaster management.

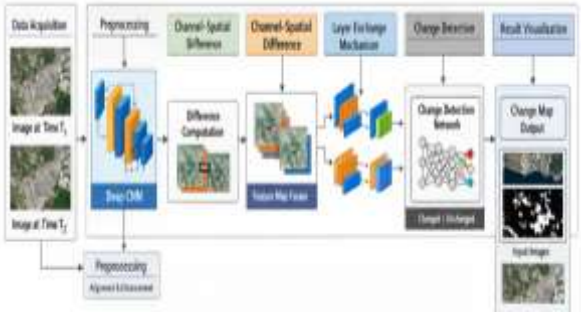


Fig 5.1: Structure of the Proposed System

VI. IMPLEMENTATION

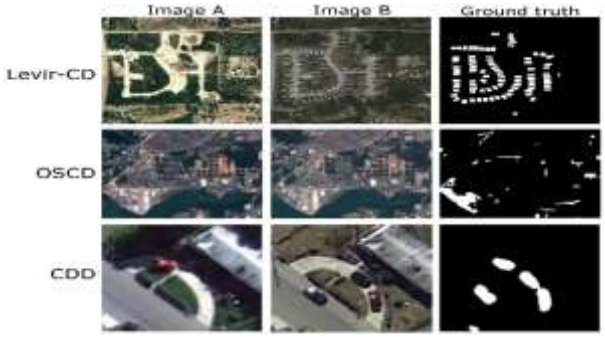


Fig 6.1: Dataset Input Interface

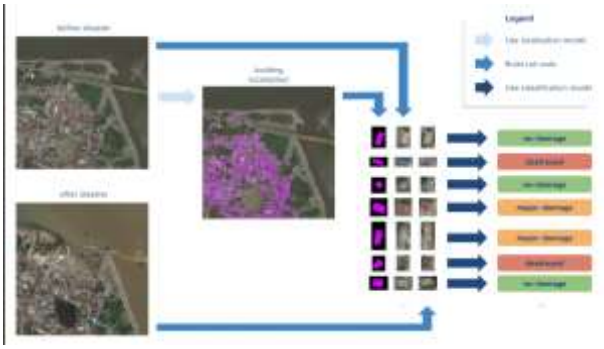


Fig 6.2: Image Preprocessing Stage

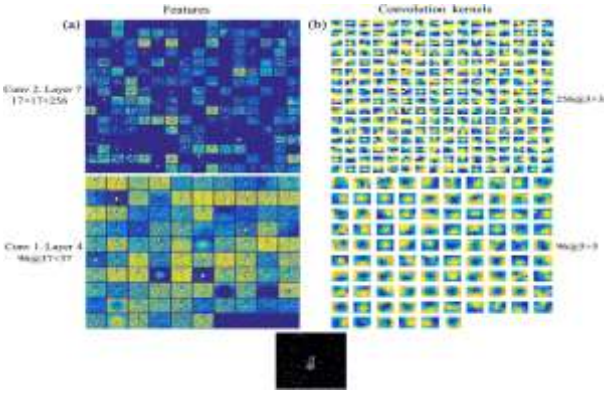


Fig 6.3: Feature Extraction using CNN



Fig 6.4: Channel–Spatial Difference Computation

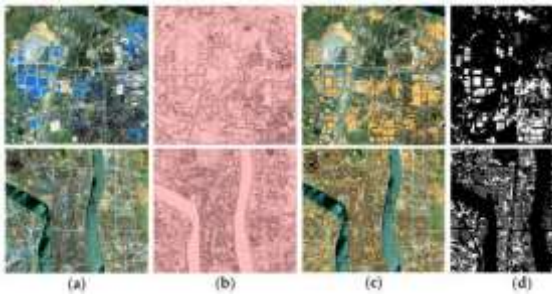


Fig 6.5: Final Change Detection Output

VII. CONCLUSION

Change detection in remote sensing imagery plays a vital role in Earth observation applications such as urban development monitoring, environmental assessment, disaster management, and infrastructure planning. Accurate identification of changes between bitemporal images is challenging due to variations in illumination, seasonal effects, atmospheric disturbances, and subtle structural differences. Traditional deep learning-based change detection models primarily focus on extracting spatial differences between two temporal images, often neglecting the rich information present in the channel dimension of feature maps. This limitation reduces their ability to detect minor or complex changes effectively.

In this project, we proposed an advanced remote sensing image change detection method by integrating a Channel-Spatial Difference Weighting (CSDW) module and a Layer-Exchange decoding structure within the LENet framework. The key innovation of the proposed system lies in its ability to compute and emphasize differences not only across the spatial dimension but also across the channel dimension. By jointly modeling spatial and channel discrepancies, the CSDW module enhances the sensitivity of the model to subtle, gradual, and large-scale changes. This dual-dimensional difference learning mechanism significantly improves feature discrimination capability.

Furthermore, the layer-exchange decoding strategy strengthens the interaction between bitemporal feature maps by enabling cross-layer information exchange. Since bitemporal images represent the same geographic region captured at different times, there exists strong inter-image correlation. The proposed decoding mechanism effectively captures temporal dependencies and spatial alignment between images, allowing the model to better utilize shared and complementary information. As a result, the overall change detection performance is enhanced.

Extensive experimental evaluations conducted on benchmark datasets such as CLCD, PX-CLCD, LEVIR-CD, and S2Looking demonstrate that the proposed LENet model outperforms conventional Siamese and encoder-decoder-based approaches in terms of Precision, Recall, F1-score, and Overall Accuracy. The model shows robustness in detecting subtle changes, handling complex real-world scenarios, and reducing false negatives. Additionally, the framework exhibits strong generalization ability across multiple datasets, proving its adaptability and effectiveness.

In conclusion, the proposed LENet architecture provides a robust, accurate, and efficient solution for pixel-level remote sensing image change detection. By integrating channel-spatial difference learning and enhanced temporal feature interaction, the system overcomes the limitations of existing methods and achieves state-of-the-art performance. This work contributes significantly to the advancement

of intelligent Earth observation systems and lays a strong foundation for future research in multi-temporal remote sensing analysis.

VIII. FUTURE SCOPE

Although the proposed deep neural network–based change detection framework provides accurate identification of changes in satellite imagery, several improvements and extensions can be explored in the future to enhance its performance and applicability in real-world remote sensing applications.

In future work, the system can be extended by integrating advanced deep learning architectures such as Transformer-based networks and attention mechanisms. These models can capture long-range spatial dependencies in satellite images and improve the detection of subtle environmental or structural changes. Additionally, incorporating multi-scale feature learning can help the system detect both small-scale and large-scale changes more effectively.

Another promising direction is the integration of multi-source remote sensing data, such as combining optical satellite images with Synthetic Aperture Radar (SAR) or hyperspectral imagery. This fusion of heterogeneous data sources can improve robustness under challenging conditions like cloud cover, shadows, or illumination variations, which often affect optical satellite images.

Future research can also focus on developing real-time or near real-time change detection systems by optimizing the deep learning model for faster processing. This can enable practical deployment in applications such as disaster monitoring, urban planning, environmental monitoring, and deforestation tracking, where timely detection of changes is critical.

Furthermore, the system can be enhanced with semi-supervised or self-supervised learning techniques to reduce the dependency on large labeled datasets. Since labeled remote sensing datasets are often limited and expensive to obtain, these approaches can allow the model to learn effectively from unlabeled data.

Finally, future implementations may include the development of a web-based or cloud-based remote sensing analysis platform that allows researchers, government agencies, and environmental organizations to upload satellite images and automatically detect changes. Such platforms can make advanced change detection technology more accessible and scalable for global monitoring applications.

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