Comparative Examination of Different Change Detection Methods for Remote Sensing Imagery

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Abstract: Land cover change analysis relies heavily on Change Detection (CD), which is the process of identifying semantic changes in satellite images taken at different dates. Several methods have been devised to identify changes in satellite photos. Simple to compute and apply, image differencing doesn't necessitate data collected from the ground.This study employs performance for change detection to examine multiple strategies that have been created by different researchers. Detecting changes in high-resolution satellite pictures is crucial for a better understanding of land surfaces. Using existing methods, reliably detecting changes in satellite pictures is a tough undertaking. Datasets utilized in the trials were the OSCD dataset and the SECOND dataset. In comparison with other techniques, RSCDNet achieved higher accuracy, precision, recall, and F1-score.

1 INTRODUCTION

Change detection, often known as CD, is a method that is utilized to recognize variations in events, features, and patterns on the surface of the ground throughout the course of time(Qiu et al., 2013). CD is utilized extensively in a variety of geoscientific domains, including but not limited to urban development also change monitoring, forest monitoring, environmental disaster prevention and map updating. Because of their extensive coverage, relevant temporal resolution, availability at various times and places, high spectral, spatial, and radiometric resolution, digital format, and the ability to be processed by computers, remote sensing (RS) data are extremely useful for the study of temporal and spatial changes in land cover and land use. In remote sensing photos, changes in land usage and land cover can be seen as variations in texture, shape, or gray levels(Bao and Guo, 2004).

Accurate change detection is crucial because of CD's significance in land cover/use. So, the efficacy and precision of the findings are heavily dependent on the CD method's capability as well as the quality of the data utilized to identify changes. In order to process the data and generate correct information layers and change maps, suitable and efficient procedures are necessary. There have been a number of investigations into RS CD algorithms(Fatemi Nasrabadi, 2019).

Finding new ways to detect changes in satellite images is motivating researchers to develop better CD techniques.In recent times, satellite images have been enhanced with CD techniques that possess strong discriminative abilities, leading to improved performance(Raza et al., 2022).Supervised and unsupervised CD are the two main categories. Although supervised methods are known to produce better outcomes, labeling training data manually is a real pain. However, unsupervised approaches are more commonly utilized in real-world applications since they automatically recognize changes(Fang et al., 2022).

In the present study, recently proposed techniques for RS CD were selected and investigated their performance on OSCD dataset and SECOND dataset.

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2 CHANGE DETECTION CHALLENGES

Change detection (CD) is a crucial approach for comprehending and identifying significant urban transformations through the utilization of available observed Earth data. Change detection is a significant application of remotely sensed data and it involves in analyzing more than two repetitive satellite images captured from same geographical earth area at different time intervals. Change detection is applied in urban planning assessments, monitoring deforestation in agricultural areas, and managing disasters, among other applications. In addition to the temporal variations observed across a land surface that contemporary techniques seek to identify in remotely sensed images, the spectral characteristics of bi-temporal images correspond to alterations within the geographical area(Chughtai et al., 2021). These modifications can be integrated in various manners and provide a detailed examination of the procedures involved in identifying the permissible alterations. Utilizing these remotely sensed images for CD presents certain challenges. Initially, there is a discrepancy in the data acquisition parameters resulting from repetitive coverage at brief intervals. Secondly, the vast array of spectral and statistical features present in these images, along with the imbalanced and integrated pixel data, represent significant challenges. The current approaches employ spectral and statistical characteristics that effectively identify changes. Nonetheless, variations in incident angle lead to changes in the spectral features during the image acquisition process. The statistical features remain constant; thus, data selection is crucial to mitigate the unwanted disturbances in the variations. Certain unnecessary alterations may also be associated with pre-processing techniques like thresholding, which involves the transformation of images.

3 REVIEW OF LITERATURE

The V-BANet deep learning technique was used to split landscapes and extract information from photos. It integrated the V-net with a Bilateral Attention Network. Independent processing of each bi-temporal image allows V-Net to detect objects in them. Additionally, features were retrieved from these segmented pictures utilizing the channel and spatial attention techniques of BANet (Prasad et al., 2023). An approach to remote sensing image change detection using supervised deep learning called multi-scale CD. Deep networks monitored by an administrator were able to identify modifications to remote sensing images. According to (Alshehhi and Marpu, 2023), it employed dice correlation between reference change maps on several scales and multi-scale forecast probability change and error functions and also used the Domain Knowledge-guided Self-Supervised Change Detection (DK-SSCD) method, which combines domain knowledge of remote sensing indices during training and inference, to enable unsupervised CD capabilities. It improved CD accuracy, reduced quality spikes, and provided a good feature representation space that highlighted changed information for bitemporal images by using contrastive learning and domain knowledge (Yan et al., 2023). The TD-SSCD method, which stands for Temporal and Differential information for Self-Supervised Contrastive Learning Change Detection, employed as an alternating iteration learning technique to progressively understand potential connections between bitemporal and their differential images. Internal to a self-supervised learning framework, this was executed (Qu et al., 2023).

A CD deep learning network that makes use of satellite pictures is called Urban CD Network (UCDNet). There was no loss of shape in the altered areas' geometry while using UCDNet to forecast their borders (Basavaraju et al., 2022). The Remote Sensing Change Detection Network is an all-inclusive DL architecture for CD using RSCDNet data. Problems with objects touching their borders and with objects of varying sizes and shapes were handled (Barkur et al., 2022). Weighted binary cross-entropy loss function is used and updated U-net with binary cross-entropy is used in identifying changes, particularly tiny ones, in complex urban settings. Databases in northern urban regions, where changes occur quickly and are monitored with often updated information, were helped by this network. This was due to its lightning-fast processing time, which allows it to produce change maps with pinpoint accuracy in a flash (Gomroki et al., 2022). One method for detecting CD in satellite pictures is the Sibling Regression for Optical Change detection (SiROC) approach, which looks at how CD pixels change over time (Kondmann et al., 2021). Deep Learning (DL) approach for CD that is highly advanced. An effective method for feature extraction and semantic segmentation, EffCDNet makes use of a pre-trained architecture.

4 METHODOLOGY

Change Detection of satellite images by various techniques(algorithms) are done as shown in the Figure 1.

The dataset OSCD and SECOND are trained by each considered technique, then trained model are tested through test sample images.

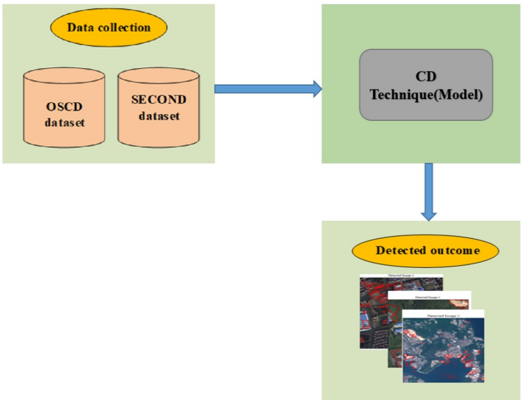

Figure 1: Change Detection Process

4.1 Data Source

The dataset is derived from two separate sources: the Onera Satellite Change Detection dataset (OSCD) and the SEmantic Change DetectiON Dataset (SECOND). OSCD is composed of multispectral images obtained from Sentinel-2 satellites. This dataset is utilized to tackle the challenge of identifying changes between satellite images. The SECOND dataset emphasizes the identification of changes in land cover and the accurate categorization of these changes with precise pixel-level delineations. The approach identifies semantic changes through the utilization of feature pairs obtained from modules with varied structures, which consider different spatial extents and quantities of parameters. The images from this dataset undergo processing to eliminate noise and correct errors during the initial pre-processing stage.

4.1.1 Onera Satellite Change Detection dataset

The dataset comprises 24 collections of images acquired from Sentinel-2 satellites during the period from 2015 to 2018. Locations are selected from various regions across the globe. Each site is provided with pairs of Sentinel-2 satellite images captured in 13-band multispectral mode. The OSCD dataset contains images with varying spatial resolutions of 10m, 20m, and 60m(Caye Daudt et al., 2019).

4.1.2 Semantic Change Detection Dataset

The dataset comprises 4662 pairs of images sourced from multiple platforms. Each image is characterized by a resolution of 512 x 512 and includes pixel-level details. The second annotation is conducted by a specialized group focused on earth vision applications, ensuring a high level of label accuracy(Yang et al., 2020).

4.2 Data Preprocessing

Images undergo pre-processing to address pixel size, resolution issues, and to eliminate unwanted noise and errors. Enhance the overall clarity of the original image. Through the analysis of neighboring pixels and their likeness, it executes adaptive filtering, thereby improving the overall quality of the image. The method successfully minimizes noise in images while preserving their structural integrity.

5 CHANGE DETECTION TECHNIQUES

5.1 EffCDNet

It is enhanced Convolution Neural Network (CNN) with preserving the efficiency and precision of segmentation within the network. An optimized architecture known as EffCDNet utilizes a siamese-based pre-trained encoder pair attached with an Attention-based UNet decoder,which performs semantic segmentation. The network utilizes a pre-trained EfficientNet architecture, incorporating shared weights to enhance feature extraction capabilities. The UNet decoder utilizes attention mechanisms and adopts the attention-gate layer just prior to the concatenation operation. This acquires more distinct relevant features to enhance the segmentation performance. The reconstruction of fine-grained feature maps, leveraging substantial context information for enhancement in the change map, employed the Undecimated Discrete Wavelet Transform (UDWT) fusion as a post-processing technique. This approach facilitated spatial and temporal analysis of multi-resolution images, resulting in a significantly improved information difference map(Patil et al., 2021).

5.2 V-BANet

Deep learning techniques that employ V-Net and Bilateral Attention Network (V-BANet) are utilized for the segmentation of landscapes and the extraction of features from images. The bi-temporal images are initially segmented using V-Net to independently identify the objects present in each image. The Bilateral

Attention Network employs spatial and channel attention blocks to enhance the extraction of discriminative features from images. The relationships among the features are elucidated through a comparison of the original feature map in one image with the modified feature map in another.(Prasad et al., 2023).

5.3 UCDNet

A deep learning model known as the urban CD network (UCDNet) has been developed for urban change detection using bi-temporal multispectral Sentinel-2 satellite images. The architecture of the model is founded on an encoder–decoder framework that incorporates modified residual connections along with the new spatial pyramid pooling (NSPP) block. The encoder unit consists of two streams that have identical structures and share weights, as demonstrated in Every input image is assigned to one of these identical structures. Similar to the FC-Siamconc network, the encoder component is made up of convolutional and pooling layers. Each stream incorporates three pooling layers. The primary goals of the CD techniques involve detecting variations between two images, with the disparity in the learned features serving as the input for the adjusted residual connection at each stage of the encoder component.The input to the NSPP block consists of features that have been learned from the encoder section. This process aids in extracting features across different ranges, providing insight into the global context(Basavaraju et al., 2022).

5.4 RSCDNet

The RSCDNet-integrated Modified Self Attention (MSA) module and Gated Linear Atrous Spatial Pyramid Pooling (GL-ASPP) block's extensive functionality. In order to remove unnecessary channel information from features at many scales, a GL-ASPP assembly uses a channel-wise descriptor in conjunction with a gated module. In order to successfully filter out abnormal information flow from the encoder to the decoder, the GL-ASPP block also accounts for channel dependencies. Careful design went into the Modified Self Attention (MSA) block so it could combine the strengths of the channel attention operation with the backbone self-attention unit. The input feature vector's spatial channel dependency is used by this operator. In contrast to the conventional self-attention module, the computed channel-self attention is passed via an attention gate to filter out extraneous data and emphasize the important parts.(Barkur et al., 2022).

5.5 IU-Net

This approach employed an enhanced IU-Net convolutional network for the purpose of change detection. The IU-Net architecture consists of two distinct pathways. The initial pathway, referred to as the encoder, is responsible for identifying the background of images, while the subsequent pathway, known as the decoder, determines the precise location of features through transposed convolution. It employs 64 3×3 double convolution kernels across five blocks, incorporating the ReLu activation function, batch normalization layers, and four 2×2 Max Pooling operators during the encoding phase. During the decoding stage, a transposed convolution with a stride of two, along with concatenation and two convolution layers utilizing a 3×3 kernel size, was employed to upsample the multiscale feature maps. Upon completion of the decoding stage, a singular 1×1 convolution layer featuring a Softmax activation function, along with weighted binary cross-entropy, is employed for the purpose of change detection. The change detection was conducted initially using RGB bands and subsequently with both RGB and NIR bands. In the analysis of the datasets, 67% of the data was allocated for training purposes, while 33% was designated for testing(Gomroki et al., 2022).

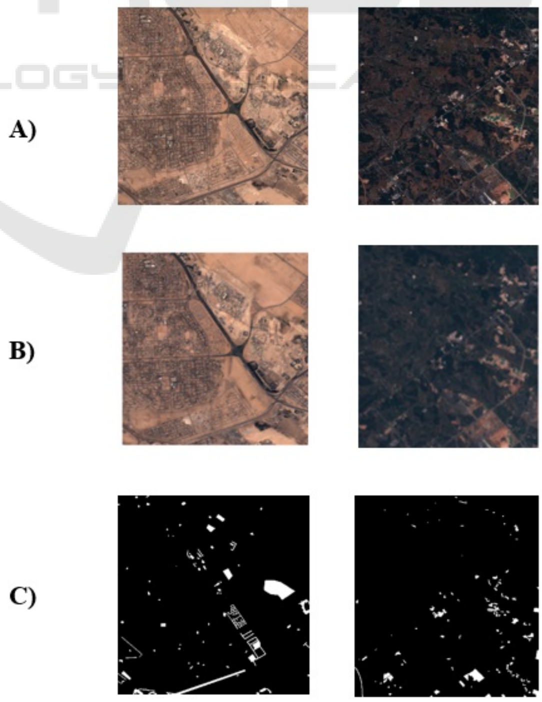

Figure 2: OSCD Dataset: A) Input Image B) Filtered Image C) Detected Image

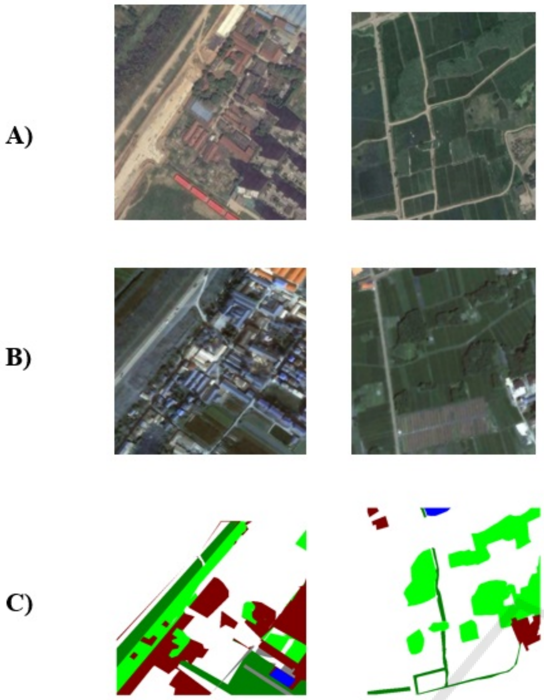

Figure 3: SECOND Dataset: A) Input Image B) Filtered Image C) Detected Image

Samples of input images, preprocessed images and change detected output images are shown for OSCD data images and SECOND data images in Figure 2 and Figure 3 respectively

6 RESULTS AND DISCUSSION

6.1 Performance Analysis for OSCD Dataset

Table 4 illustrates several performance metrics of OSCD dataset. EffCDNet model achieved an accuracy of 92.6%, with corresponding precision, recall, IoU and F1-score of 92.6%, 87.7%, 98% and 89.2%, respectively. V-BANet transformer model demonstrated high performance across all metrics, attaining precision of 98.93% along with accuracy, IoU, recall and F1-score of, 99.29%, 98.31%, 98.96%, 98.87%. Similarly, UCDNet model showed recall at 86.16%, with precision, accuracy, kappa co-efficient and F1-score of 95.53%, 99.30%, 88.85% and 89.21%. IU-Net model achieved F1-score of 98.65% along with precision, recall, IoU and accuracy of 98.64%, 98.64%, 97.34% and 97.38%. RSCDNet achieved an accuracy of 99.2% with recall, F1-score, IoU, kappa co-efficient and precision of 99%, 99.1%, 96%, 98.10% and 99% respectively.

The performance analysis of various techniques is shown in the graph figure 4 for OSCD. here comparison is shown for accuracy parameter.

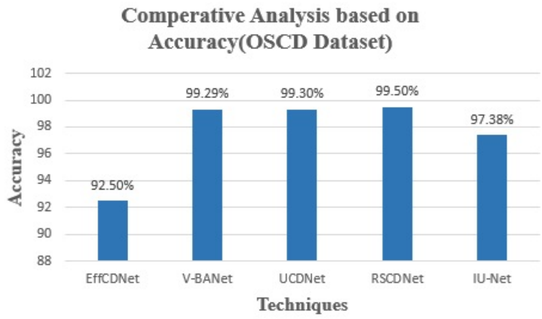

Figure 4: Analysis on OSCD Data

6.2 Performance Analysis for SECOND Dataset

Table 5 illustrates several performance metrics of SECOND dataset. EffCDNet model achieved an accuracy of 91.5%, with corresponding precision, recall, IoU and F1-score of 94.6%, 85.5%, 95% and 88.6%, respectively. V-BANet transformer model demonstrated high performance across all metrics, attaining precision of 96.83% along with accuracy, IoU, recall and F1-score of, 97.29%, 96.31%, 97.6%, 98.5%. Similarly, UCDNet model showed recall at 85.25%, with precision, accuracy, kappa co-efficient and F1-score of 96.5%, 98.78%, 87.8% and 89.30%. IU-Net model achieved F1-score of 97.6% along with precision, recall, IoU and accuracy of 97.4%, 98%, 97.5% and 96.80%. RSCDNet achieved an accuracy of 98.25% with recall, F1-score, IoU, kappa co-efficient and precision of 98.50%, 98.7%, 97%, 98.30% and 98% respectively. The performance analysis of different techniques is shown in the Table 1.

The performance analysis of various techniques is shown in the graph figure 5 for SECOND. here comparison is shown for accuracy parameter.

7 CONCLUSIONS

The discussion focuses on prevalent techniques for detecting changes for satellite images and the approach of change detection following classification. This paper proceeds from the principles of them, analyzing their results and comparing them with respect to performance parameters such as accuracy, precision, recall, F1-Score, IoU (Intersection over Union),

Table 1: Performance Analysis on OSCD Data

Techniques	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	IoU (%)	Kappa co-efficient (%)
EffCDNet	92.5	92.6	87.7	89.2	98	-
V-BANet	99.29	98.93	98.95	98.87	98.31	-
UCDNet	99.30	95.53	86.16	89.21	-	88.85
RSCDNet	99.5	98.40	98.30	98.20	96	98.10
IU-Net	97.38	98.64	98.64	98.65	97.34	-

Table 2: Performance Analysis on SECOND Data

Techniques	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	IoU (%)	Kappa co-efficient (%)
EffCDNet	91.5	94.6	85.5	88.6	95	-
V-BANet	96.83	97.29	96.31	97.6	98.5	-
UCDNet	96.5	98.78	87.8	89.30	-	88.85
RSCDNet	98.5	98.7	97	98.30	96	98
IU-Net	97.4	98	97.5	96.8	97.6	-

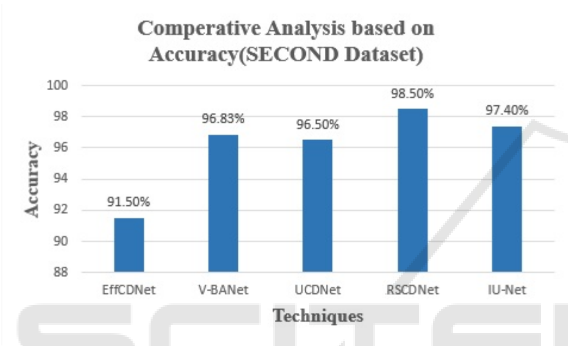

Figure 5: Analysis on SECOND Data

and Kappa. Two data sets are selected for experimentation: OSCD and SECOND. The different CD techniques proposed by various experts are implemented and analyzed on the chosen dataset. Among EffCDNet, V-BANet, UCDNet, RSCDNet, and IU-Net, RSCDNet demonstrated superior performance, achieving an accuracy rate of 99.5%.

REFERENCES

Alshehhi, R. and Marpu, P. R. (2023). Change detection using multi-scale convolutional feature maps of bi-temporal satellite high-resolution images. *European Journal of Remote Sensing*, 56(1):2161419.

Bao, Q. and Guo, P. (2004). Comparative studies on similarity measures for remote sensing image retrieval. In *2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat. No. 04CH37583)*, volume 1, pages 1112–1116. IEEE.

Barkur, R., Suresh, D., Lal, S., Reddy, C. S., Diwakar, P., et al. (2022). Rscdnet: A robust deep learning architecture for change detection from bi-temporal high resolution remote sensing images. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 7(2):537–551.

Basavaraju, K., Sravya, N., Lal, S., Nalini, J., Reddy, C. S., and Dell'Acqua, F. (2022). Ucdnet: A deep learning model for urban change detection from bi-temporal multispectral sentinel-2 satellite images. *IEEE Transactions on Geoscience and Remote Sensing*, 60:1–10.

Caye Daudt, R., Le Saux, B., Boulch, A., and Gousseau, Y. (2019). Oscd - onera satellite change detection.

Chughtai, A. H., Abbasi, H., and Karas, I. R. (2021). A review on change detection method and accuracy assessment for land use land cover. *Remote Sensing Applications: Society and Environment*, 22:100482.

Fang, H., Du, P., and Wang, X. (2022). A novel unsupervised binary change detection method for vhr optical remote sensing imagery over urban areas. *International Journal of Applied Earth Observation and Geoinformation*, 108:102749.

Fatemi Nasrabadi, S. B. (2019). Questions of concern in drawing up a remote sensing change detection plan. *Journal of the Indian Society of Remote Sensing*, 47(9):1455–1469.

Gomroki, M., Hasanlou, M., and Reinartz, P. (2022). Iunet-ucd: Improved u-net with weighted binary cross-entropy loss function for urban change detection of sentinel-2 satellite images.

Kondmann, L., Toker, A., Saha, S., Schölkopf, B., Leal-Taixé, L., and Zhu, X. X. (2021). Spatial context awareness for unsupervised change detection in optical satellite images. *IEEE Transactions on Geoscience and Remote Sensing*, 60:1–15.

Patil, P. S., Holambe, R. S., and Waghmare, L. M. (2021). Effcdnet: Transfer learning with deep attention network for change detection in high spatial resolution satellite images. *Digital Signal Processing*, 118:103250.

Prasad, J., Sreelatha, M., and SuvarnaVani, K. (2023). V-banet: Land cover change detection using effective deep learning technique. *Ecological Informatics*, 75:102019.

Qiu, L., Gao, L., Ding, Y., Li, Y., Lu, H., and Yu, W. (2013). Change detection method using a new difference image for remote sensing images. In *2013 IEEE International Geoscience and Remote Sensing Symposium - IGARSS*, pages 4293–4296.

Qu, Y., Li, J., Huang, X., and Wen, D. (2023). Td-sscd: A novel network by fusing temporal and differential information for self-supervised remote sensing image change detection. *IEEE Transactions on Geoscience and Remote Sensing*.

Raza, A., Huo, H., and Fang, T. (2022). Eunet-cd: Efficient unet++ for change detection of very high-resolution remote sensing images. *IEEE Geoscience and Remote Sensing Letters*, 19:1–5.

Yan, L., Yang, J., and Wang, J. (2023). Domain knowledge-guided self-supervised change detection for remote sensing images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 16:4167–4179.

Yang, K., Xia, G.-S., Liu, Z., Du, B., Yang, W., Pelillo, M., and Zhang, L. (2020). Semantic change detection with asymmetric siamese networks.