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Artificial Neural Networks (ANNs) used for change detection in remotely sensed images

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Abstract: This paper examines the application of semi-supervised Artificial Neural Networks (ANNs) in the change detection of remotely sensed images. Relying on the analysis of multi –temporal satellite images to detect altercations caused by natural or human activities is crucial for change detection for monitoring environmental changes and urban expansion. Recent advancements in Artificial Intelligence (AI) particularly semi-supervised ANNs, have significantly improved the accuracy and efficiency of change detection processes. This review highlights various methodologies and techniques employed in the field, including the integration of Convolutional Neural Networks (CNNs) and Graph Convolutional Networks (GCNs) for enhanced feature extraction and classification. The paper discusses the application of these methods across different scenarios such as agricultural yield prediction, urban growth monitoring and environmental surveillance underlining the importance of ANNs in advancing remote sensing capabilities.

Keywords*: Change detection, remote sensing, ANNs, urban areas, applications,*

1. Introduction

In remote sensing, tracking environmental changes, and land use/land cover change detectionis an essential procedure. It entails examining how natural or artificial factors have affected the spatial composition of satellite images. Over the years, numerous techniques have been devised, and more are always being worked on. Assessing human-natural interactions and resource management is made easier with well-timed and particular change detection of Earth's surface functions. Multi-temporal datasets are used in change detection to quantitatively examine how events change over time (Asokan et al., 2019).Although change detection is a necessary technique in remote sensing, there isn't a thorough analysis of the topic. An overview of the main change detection methods and their historical evolution is given by (Hecheltjen et al., 2014). The process chain and how it can be modified to meet specific needs are also covered. Pre-change extraction labelling, contemporaneous labelling, and post-change extraction labelling are the three new change labelling categories that are presented. Time series analysis techniques are also reviewed; these were not covered in earlier assessments. Moderate resolution satellite imagery with time series analysis is becoming more and more common since it may increase the accuracy of remote sensing and reveal changes in the terrain. This is mostly true when using Landsat data. This trend offers near real-time monitoring benefits by extending land surface monitoring to minor changes in ecosystem health and land use dynamics. Future directions will emphasise bigger area applications, temporal accuracy, and the use of many sensors (Woodcock et al., 2020).To determine the temporal and spatial changes that have happened as a result of natural or artificial processes, satellite photographs of the earth's surface are examined. Understanding of land cover, environmental changes, habitat fragmentation, coastal alteration, city sprawl,etc. is provided by real-time forecast of change (Afaq and Manocha, 2021). There are numerous approaches used for change detection remote sensing as shown in Fig. 1, includes algebra based approach, transform based approach, advance model, GIS, classification based approaches.

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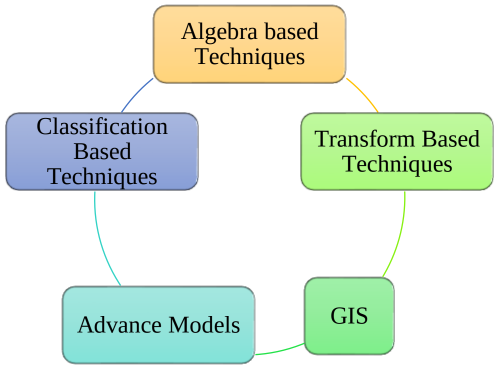

Fig. 1 Different techniques of change detection for remote sensing

The growing need for data on Earth's surface is essential for many uses, such as environmental studies, resource monitoring, and land-use change monitoring. For investigations on change detection, satellite data from remote sensing provides a range of resolutions. Addressing various techniques inclusive of object-based, pixel-based, data-oriented, and spatial information mining,(Hussain et al., 2013) the significance of multiple sensors and the exponential growth in image data quantity is highlighted. Object based techniques and data mining techniques maintain promise in trade detection, mainly with the increased use of Very high-resolution (VHR) images. Remote sensing techniques are gaining traction in research owing to the growing demand for real-time data on land surface phenomena. Satellite structures, by collecting environmental data at exclusive resolutions, can discover modifications in the surrounding area, important for information human-nature interactions and decision-making depending on real-time sensing. Trade detection encompasses complex steps which includes algorithm selection, image preparation, problem identification, and variable usage (Deilami et al., 2015). Remote Sensing Change Detection (RSCD) is the technique of identifying differences among scenes captured at specific instances in the identical area, holds great ability with various applications and is currently under active research. The literature reviews a big range of change detection strategies ranging from basic differencing to machine learning algorithms. Efforts have been made by lecturers to categorize these techniques in order to streamline and arrange the problem. Several category schemes have been proposed based on different factors, dimensions, or traits of the techniques(Si Salah et al.,2020). However, practitioners nonetheless find it difficult to make use of these schemes efficiently to comprehend the varied techniques and pick suitable strategies for specific remote sensing change detection tasks.

Application of Artificial Neural Networks in Remote Sensing

A new MSG-GCN model for classifying forest types from aerial images is provided by using (Pei et al., 2023). To extract high- and low-stage functions, it uses multi-scale convolutional kernels, an MSGCN module (Los Angeles) and output functions from various deciphering blocks. Without interference from low-stage functions, the model learns co-relations between neighbouring pixels in irregular areas with success.Data structure conflict between convolution and graph convolution is fixed by the MSGCN module. For feature learning on both small- and large-scale irregular areas, CNN and GCN are utilised. Moreover, the study suggests that NMXs and CPs are more likely than NBLs to be incorrectly categorised. One of the most difficult tasks in image evaluation is the categorization of Hyper Spectral Remote Sensing Images (HRSIs). Convolutional Neural Networks (CNNs), particularly, have established amazing performance in HRSI category when used in deep learning. In order to overcome the problem,(Fırat et al., 2023) indicates utilizing the Hybrid 3D/2nd CNN technique along with the Hybrid 3D/2nd complete Inception module. In an effort to lessen computational complexity and extract more spatial functions, the recommended method employs several convolution layers with the Inception module for multi-stage function extraction. Pre-processing with PCA ensures the best possible spectral band extraction. Tests conducted on datasets from Indian pines, Salinas, University of Pavia, HyRANK-Loukia, and Houston showed that the method performed better in classification than state-of-the-art techniques, with overall accuracy of 99.83%, 100%, 100%, 90.47%, and 98.93%.For remote sensing image Super Resolution (SR) (Liang et al., 2023) suggest a Multi-scale hybrid Attention Graph Super Resolution (MAGSR). Large size differences and great complexity are used by the MAGSR method to extract multi-scale deep functions and high-frequency detail information. To understand spatial dependency on each channel, it integrates channel and spatial attention. When compared to the inferior approach DRCAN, the MAGSR algorithm improves PSNR by 0.03 dB and achieves the highest SSIM and PSNR values on the Google dataset.

According to experimental data, MAGSR outperforms other popular SR techniques and can reconstruct crisp, visually striking SR remote sensing images.In order to enhance remote sensing scene categorization (RSSC) on satellites, Zhang et al. (2023) suggest using an All Adder Neural Network (A^2 NN) with a generative-based hybrid knowledge distillation (GHKD) training technique. Compared to conventional CNNs, the A^2 NN has lower resource overheads because it is made up of adder kernels. In contrast to CNNs, it has a lower RSSC accuracy. A hybrid KD technique and a generative learning technique is based primarily on knowledge matching are mixed inside the GHKD training plan. While the knowledge-matching-based on generative learning technique produces useful samples, the hybrid KD method passes high-performance type knowledge from the CNN to the ANN. The GHKD training technique dramatically complements the RSSC overall performance of the A^2NN accomplishing similar overall performance to CNNs on maximum datasets as verified by significant testing on six public RSSC datasets. For farmers, legislators, and meals processing facilities, predicting agricultural yields is important as it allows them make money from the products they develop. It might be difficult to pick the correct independent variables, though. The application of Artificial Neural Networks (ANNs) to agricultural crop yield prediction is included by (Hara et al., 2021), with an emphasis on environmental factors along with soil parameters and climate data. according to (Ballesteros et al., 2020), the mixture of Vegetation Indices (VIs) and Vegetated Fraction Cover (Fc) to predict vineyard yields led to higher accuracy (RMSE=0.9 kg vine−1 and relative error =21.8% for the image when close to harvest) as compared to simple VIs, according to the results of a vineyard study using pc vision techniques and Artificial Neural Networks (ANN). When deep learning techniques had been used in location of linear models, the output estimates have been more correct and yielded pictures that have been taken closer to the results date. The use of Convolutional Neural Networks (CNN) for semantic segmentation of remote sensing photographs is included by the researcher (Alam et al., 2021). The combination of signs and methodology of U-Net-CNN comes from the SegNet authorities used to increment the semantic segmentation. The technique, makes use of the section shape or the combination of the 2 models for reinforcing the segmentation procedure.The combined technology used in the Einzelmodell has a maximum impact of 90.2% and 88.1% and 87.0%.While SegNet's accuracy is 93% and 89.6% more than U-net's 85.4%, U-net's accuracy is 89.3% better than SegNet's 85.4 %. For buildings and roads, the model included algorithm achieves accuracy of 91.5% and 90.7%, respectively. Convolutional Neural Networks (CNNs), specially are deep learning algorithms that are being employed increasingly more for high spatial resolution remote sensing image recognition. However these algorithms often inherit the network structure without taking HRS image specificity and complexity into account.(Wang et al., 2020) suggests a deep Neural Network (RSNet) framework for remote sensing that robotically searches for the best network structure for challenges involving the detection of HRS images. With its outstanding computing performance and appropriate accuracy, the RSNet is a good preference for processing HRS images. Huge remote sensing data, which can be utilised for climate change assessment, disaster prediction, land cover category, and regional making plans, has expanded due to remote sensing technology. Data processing is tough due to the disparate resolutions, imaging modes, and sensor types that characterise this data. (Boulila et al., 2021) offers a distributed deep learning-based technique for managing RS image classification (RS-DCNN), specifically distributed Convolutional-Neural-Networks for processing big remote sensing images. Across the huge data cluster, the method employs a pixel-based Convolutional Neural Network (CNN) model and tests on a real dataset in Saudi Arabia demonstrate splendid type accuracy at a faster rate. Moreover, Table 1 provides the comparative evaluation of latest studies carried out for remote sensing with the help of artificial intelligence techniques.

Table 1:Recent studies conducted using Artificial Intelligence in remote sensing

Study Reference	Focus of Study	Methodology Employed	Key Features and Techniques	Key Numerical Findings (if provided)	Observations and Conclusions
Pei et al. (2023)	Forest type classification from aerial photos	Multiscale Graph Convolutional Neural Networks (MSG-GCN)	Uses multiscale convolutional kernels, an MSGCN module, LA, and output features for learning pixel correlations	N/A	Successfully resolves data structure conflicts; effective for small and large area classification
Fırat et al.	Hyperspectral	Hybrid 3D/2D	Multi-level feature	Overall accuracy:	Superior

(2023)	remote sensing image classification	CNN with Complete Inception module	extraction, PCA for spectral band extraction	99.83%, 100%, 100%, 90.47%, and 98.93% on various datasets	performance in HRSI classification; reduces computational complexity
Liang et al. (2023)	Remote sensing image super resolution	Multi-scale Hybrid Attention Graph Super Resolution (MAGSR)	Multi-scale feature extraction, hybrid attention mechanism	Improves PSNR by 0.03 dB; highest SSIM and PSNR values on Google dataset	Outperforms traditional SR methods; enhances detail extraction
Zhang et al. (2023)	Remote sensing scene categorization	All Adder Neural Network (A2 NN) with GHKD training technique	Utilizes adder kernels, hybrid KD approach, and generative learning	Comparable performance to CNNs on most datasets	Reduces resource overhead; effective for RSSC with GHKD training
Hara et al. (2021)	Agricultural crop yield prediction	Artificial Neural Networks (ANNs)	Focus on environmental factors such as soil parameters and climate data	N/A	Demonstrates the utility of ANNs in predicting agricultural yields
Ballesteros et al. (2020)	Vineyard yield prediction	ANNs with vegetation indices (VIs) and vegetated fraction cover (Fc)	Combines VIs and Fc for improved accuracy	RMSE=0.9 kg vine−1; Relative error=21.8%	Enhances accuracy of vineyard yield prediction with ML approaches
Alam et al. (2021)	Semantic segmentation of remote sensing images	Enhanced SegNet with index pooling and U-net structures	Integrated approach for multi-target semantic segmentation	Overall accuracy: 90.2%; Buildings: 91.5%, Roads: 90.7%	Improves segmentation accuracy compared to single model approaches
Wang et al. (2020)	High spatial resolution image detection	Deep Neural Network (RSNet)	Searches for the best network architecture for HRS image detection challenges	N/A	Provides efficient processing for HRS images with acceptable accuracy
Boulila et al. (2021)	Remote sensing image classification	Distributed Deep Learning (RS-DCNN)	Distributed CNN for large remote sensing images, pixel-based model	Demonstrates high classification accuracy at a faster rate	Effective for processing large datasets with diverse resolutions and sensor types

This comparative table provides an overview of recent studies inside the utilization of artificial intelligence strategies to remote sensing and agricultural yield prediction. It outlines the focus on every observation, methodologies applied, key features, numerical findings, and conclusions. The research range from classifying forest sorts from aerial pics to improving remote sensing image resolution and predicting agricultural yields the use of synthetic neural networks.

2. Detecting Change in Urban Areas

The process of remote sensing change detection uses contrasts between several multi-temporal photographs acquired over the same area to discover changes in the earth's surface. Studying national economies, ecosystem reactions to natural and artificial forces, and the scope and pace of urban expansion are all aided by this method (Giustariniet al., 2012). In densely urbanised areas, remotely sensed data offers an appropriate spatial and temporal framework for charting urban development, facilitating quantitative and systematic monitoring and management. Earth orbiting satellites play a critical role in monitoring the earth's surface throughout time by taking consistent, high-quality images at regular intervals and across the whole seasonal cycle (Reba and Seto, 2020). Because aerial photography has a great spatial resolution, it is the standard approach for studying urban growth. However, it is challenging and expensive to follow up with this strategy because of the increased urbanisation that is occurring in emerging nations (Fyleris et al., 2022). Compared to aerial photography or ground surveys, advances in space technology, satellite images, and digital image processing enable low-cost and high-temporal resolution urban studies (Si Salah et al., 2019).

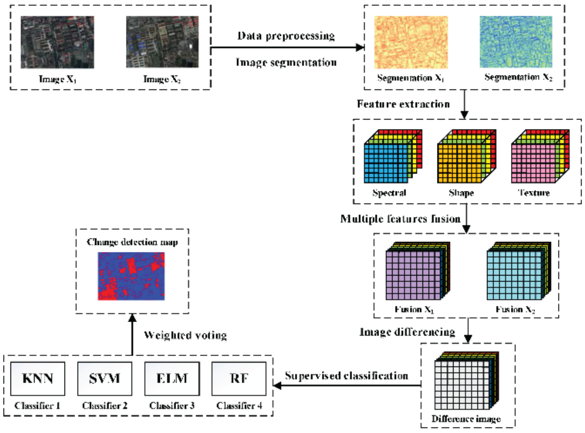

Fig. 2 Change detection based on objects in urban area

The following phases are generally included in the suggested by Wang et al. (2018), which is depicted in Fig. 2. Pre-processing of the data is done to lessen differences between bi-temporal images. To create segmentation maps of bi-temporal pictures, image segmentation is done. A difference picture is created when the spectral, shape, and textural information of the homogenous pixels represent the features in each section of the images. The difference image is used to identify changes using a number of supervised classifiers, and the output of these classifiers is combined to provide the final result.Although the majority of knowledge about urban areas is local, urbanisation is a crucial role in environmental change on a worldwide scale. Urban expansion can be remotely sensed to gather data on temporal and spatial growth trends. This data is crucial to comprehending the political and inexpensive forces influencing development in addition to the results these factors have on the environment, society, and climate. However, due to their limited footprints, numerous material compositions, and varying development costs, urban areas are difficult to map across the world. Data from the moderate resolution Imaging Spectro-Radiometer (MODIS) is used by (Mertes et al., 2015) to illustrate a technique for monitoring the spread of urban land at continental to global scales. With appropriate accuracy, this technique resolves spectral and temporal ambiguities between stable and altered regions and concrete/non-urban land under a number of socioeconomic, political, and ecological/climatic contexts. Because of their variable flying speed and complicated system like laser scanners, inertial navigation structures, and radar altimeters, helicopters make high-quality sensor structures. Change detection and terrain-referenced navigation are other uses for these devices. (Hebel et al., 2013) proposes a framework for real-time evaluation between reference data from an urban region and the data from an aerial laser scanner (ALS). The technique expands on the idea of occupancy grids from robotic mapping while retaining the accuracy of measured data on grid cells. The Dempster-Shafer theory is used by the suggested alternate detection technique to discover contradicting data alongside the laser pulse propagation course. To check if observed versions are seasonal or man-made, extra traits are taken into consideration. Through offline tests the use of ALS data that was captured, the concept of online change detection has been confirmed. (Hu Ban et al., 2014) describe a technique for the analysis of log ratios in multi-temporal single-polarization Synthetic Aperture Radars (SAR), all automated and efficient.The technology uses the histograms and consists of a unimodal and bimodal test. The various modalities are based on the values of the primary components that use the general technology of Kittler and Illingworth Thresholding (GKIT), which are based on the general Gaussian model (GG-GKIT).The image is segmented into small sections and a multiscale region selection technique is used to select regions with a balanced mixture of altered and unaltered classes if the histogram is unimodal. The selected areas are mixed to create a new histogram, and in the log-ratio, the ideal threshold value is implemented to differentiate between modified and unaffected pixels.For maps to be updated, items like buildings must be detected when they change. Traditionally, spectral analysis of multi-temporal pictures has been used for detection. A strategy using multi-temporal interpolated lidar data is proposed by Teo and Shih (2013). This project aims to use geometric analysis for change detection and change-type identification. Between the digital surface models in two distinct time periods, a form difference map is produced. Little form variations are regarded as unaltered areas and are not included in the segmentation process. The change kinds are then determined by applying the characteristics of the item. Numerous techniques involved in detecting change in urban areas which were mentioned in Table 2. This table shows involved techniques and focus of researchers.

Table 2 Change detection techniques in urban areas

Study	Focus	Technique Used	Methodology	Application Area	Observations
Si Salah et al. (2019)	Urban growth monitoring	Space technology, satellite images	Digital image processing	Urban studies	Provides low-cost, high-temporal resolution urban studies compared to traditional aerial photography.
Wang et al. (2018)	Change detection in urban areas	Bi-temporal image analysis	Data pre-processing, image segmentation, supervised classifiers	Urban change detection	Combines classifier outputs to identify changes, addressing local knowledge needs in urban expansion.
Mertes et al. (2015)	Tracking urban land expansion	MODIS data analysis	Spectral and temporal analysis	Global urban monitoring	Resolves spectral and temporal ambiguities effectively across various contexts.
Hebel et al. (2013)	Real-time urban change detection	Aerial laser scanning (ALS)	Occupancy grids, Dempster-Shafer theory	Terrain-referenced navigation	Implements real-time change detection with high accuracy, utilizing advanced helicopter equipment.
Hu and Ban (2014)	Change detection in SAR images	Synthetic Aperture Radar (SAR)	Bimodality test, GKIT thresholding technique	Map updating	Efficient automatic thresholding method for updating maps based on SAR images.
Teo and Shih (2013)	Detection of changes in buildings	Interpolated LiDAR data	Geometric analysis between digital surface models	Change detection in buildings	Uses geometric analysis for detecting changes and identifying change types in buildings.

The methodologies, procedures, and critical findings of several studies on change detection strategies in remote sensing throughout numerous software domains are highlighted in this comparative table. It summarises the improvement of remote sensing from aerial pictures to state-of-the-art satellite snap shots and computer image processing, with a focus on environmental impact evaluations, land cover adjustments, and urban expansion monitoring. Each study offers a specific angle at the challenges related to mapping urban areas, the precision of change detection strategies, and the possibilities of combining several technologies to enhance observation and analysis.

3. Aspects of Variance in the Identification of Urban Change

In the domain of urban change detection, various researchers have undertaken efforts to categorize change detection (CD) methodologies. Despite these efforts, existing classification frameworks have not encompassed the entire spectrum of diversity found across different studies and techniques. Commonly, these classifications in existing literature tend to focus predominantly on limited aspects such as the analysis unit (comparing pixel versus object) or the nature of the input data. In this context, a comprehensive classification scheme for change detection based on remote sensing in urban environments is proposed by(Si Salah et al., 2019). This new scheme evaluates multiple critical dimensions concurrently, derived from extensive analysis of numerous studies. These dimensions, delineated in the subsequent sections, include objective, input data, temporal resolution, unit of analysis, target output unit, building features, processing techniques, categories of change, and evaluation of outcomes. An illustrative overview of these dimensions, including further breakdowns into sub-dimensions, is provided in Figure 1, followed by detailed descriptions for each identified dimension.

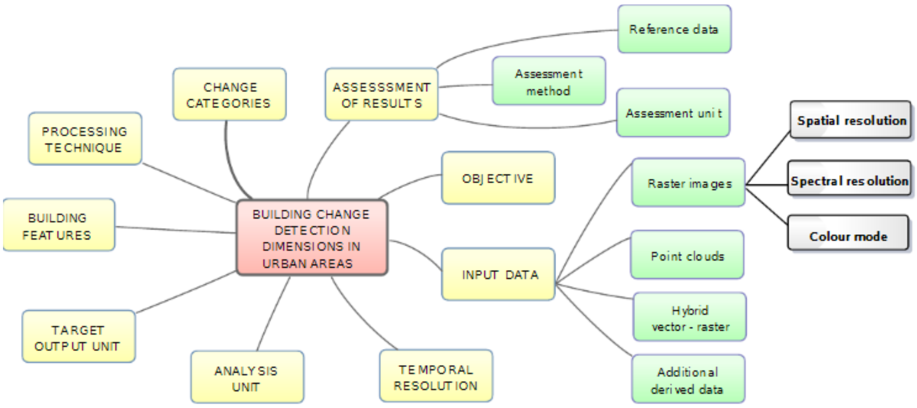

Fig. 3 Different dimensions for change detection

When compared to medium- and low-resolution photos, VHR images offer a strong guarantee for tracking finer Earth changes since they contain an abundance of image features and spatial distribution information, including the colours, textures, and structure information of the ground objects. Nonetheless, intricate environments and significantly disparate scales of identified objects represented in VHR pictures present fresh difficulties for Remote Sensing Change Detection (Xu et al., 2021)). Since pixel-based approaches rarely take spatial and contextual information into account while analysing image changes, they might not perform well on VHR images. While object-based approaches somewhat compensate for the shortcomings of pixel-based approaches, the majority of them extract change information using low-level features (such as spectrum, texture, and shape), which are not well suited to express the semantic information of VHR images. Moreover, conventional pixel- and object-based techniques rely heavily on empirically developed feature extraction algorithms, which are not scalable or flexible and necessitate a great deal of human intervention, failing to produce acceptable outcomes for VHR images.

Change detection technology works in the following ways. Image registration is used as a preprocessing step on raw RS images to guarantee coordinate system consistency. The relevant image feature extraction algorithms extract the multi-temporal information, or basic features, based on the attributes and description of the registered RS images. It includes the images' colour, texture, shape, and spatial relationship characteristics (You et al., 2020). The position and strength of the extracted change information are then revealed by the changing features, which have been improved upon or distinguished from the multi-temporal fundamental features. Change information extraction is the term used to describe the two stages mentioned above together. In order to merge global features with the shifting judgement criteria and produce the final change results, feature integration and information synthesis are finally carried out (Chen et al., 2020).

4. Computational Complexity and Resource Requirements

Combining network structures and general structures enables the implementation of artificial intelligence (AI) change detection for a variety of applications. The training set size, intended change map, and multi-period data input type must be taken into consideration right through the AI model's development. For data that is heterogeneous, a pseudo-siamese structure or mapping transformation-based structure are advised. For from-to change maps, post-classification framework is the best solution. Reliance on data from the ground can be minimized using AEs and GANs, as well as transfer learning-based structures (Karantzalos, 2015). RNN model and multi-model integrated framework are usually used to implement detection of changes on the basis of long-term sequence data. CNNs are the ideal option when there are enough training data because of their powerful feature extraction capacity. The RS community has experienced significant progress with AI techniques; however, non-linear optimization challenges, complicated structures for data, and highly dimensional data sets present difficulties. Massive training samples are required for controlled AI techniques, and these can be frequently obtained through labor-and timeconsuming methods.Unsupervised AI techniques need to be developed to overcome these challenges (Shi et al., 2020).The subpixel generation algorithms adapt well to subpixel generation algorithms based on the concept of change detection. Therefore, images are based on functional data base algorithms such as SIFT or SURF. In images from the nadir, like images from Worldview, you can use basic data algorithms to create clear images.Our investigation is a robust and effective register algorithm for images beyond the nadir at the entrance (Kwan, 2019). A robust register algorithm for Forscher, as CE and no linear, NN is composed by the researcher (Liu et al. 2019). To obtain the effectiveness tests, researchers have developed an experience of understanding and compressing the bandwidths of each of the larger PCA bandwidth tests, the efficiency test algorithm is integrated directly into the radiation domain and it develops a rapid anomaly detector and recursive implementation that depends on the random down sampling.The parallel architecture of multi-core processors and GPUs constitutes a rich solution for local change identification (Mandal and Vipparthi, 2021). To obtain more information about the discriminatory characteristics, the self-attention module automatically calculates the value of the weightsof the pixels in various positions and time.The network models spatial-temporal interactions using a CD self-attention mechanism, enabling more accurate representations of objects with varying sizes. The proposed solution beats previous cutting-edge strategies on a publicly accessible CD dataset, raising the baseline model's F1-score from 83.9 to 87.3 with an acceptable computational overhead. Change detection (CD) is critical for understanding land surface changes using Earth observation data. Deep learning is widely used for remote sensing, despite the fact that most methodologies have error accumulation concerns. U-Net++, a modern CD technique, employs an encoder-decoder structure for semantic segmentation to analyze changes maps from scratch the use of annotated datasets. The method employs co-registered image pairs for high spatial accuracy and fusion strategies for many semantic stages. Experimental results advise that it outperforms other modern CD strategies (Peng et al., 2019). (Mou et al., 2018) proposed a unique recurrent Convolutional Neural Network (Re-CNN) structure for detecting modifications in multispectral images. The structure blends convolutional and recurrent neural networks right into a single network that generates targeted spectral-spatial feature representations and analyses temporal dependency in temporal pictures. It can be trained from begin to end, uses spatial statistics intuitively, and learns temporal dependence among images adaptively. This is the first recurrent convolutional network architecture designed for multitemporal remote sensing picture evaluation. (Alcantarilla et al., 2018) implemented a configuration system the usage of Street-View videos to mount a monophonic digicam with an effective and efficient tuning chart for high-velocity independent navigation. The method uses a SLAM fusion multi-sensor and a simple three-D rendering channel that complies with the layout due to the DN architecture.

The approach outperforms present literature on a larger change detection dataset and panoramic change detection dataset. For optical aerial pictures, (Zhan et al., 2017) advocate a unique method to supervised change detection that uses a deep siamese convolutional network.By directly extracting characteristics from image pairings, the approach makes the features more robust and abstract. In order to identify differences between image pairings, the weighted contrastive loss function supports distinct feature vectors. In terms of F-measure, the method with simple threshold segmentation and k-nearest neighbour approach surpasses state-of-the-art methods.

- • The training set size, intended change map, and multi-period data input type should all be taken into account throughout the AI model's creation.
- Transfer learning-based structure and the use of AEs and GANs can reduce dependence on ground truth.
- AI techniques have achieved success in the RS community, but challenges related to high-dimensional datasets, complex data structures, and nonlinear optimization problems need to be developed.
- Researchers have experimented with compressing hundreds of bands into ten or fewer bands using PCA, developing target detection algorithms directly in the radiance domain, and developing fast anomaly detectors.
- Change detection algorithms rely heavily on registration accuracy, which can reach sub-pixel accuracies.
- More research is needed to develop robust and accurate registration algorithms for off-nadir images.

  Future guidelines consist of compressing multiple bands into ten or fewer bands by the usage of PCA, developing target detection algorithms immediately within the radiance area, and growing fast anomaly detectors.

5. Conclusion

The use of semi-supervised artificial neural networks for remote sensing alternate detection marks a massive step forward in environmental tracking and concrete planning. This studies examined several studies that demonstrated the performance and accuracy of artificial neural networks (ANNs) in analysing multi-temporal satellite photographs to locate changes in the earth's floor. The tested techniques, together with the MSG-GCN version and the Hybrid 3D/2D CNN technique, display the potential of AI to enhance change detection competencies when compared with past previous methods. Issues like as computational complexity, data quantity, and the need for precise photograph registration were explored. Future studies should give attention to increasing set of algorithm performance, minimising resource necessities, and creating sturdy models for plenty of environmental scenarios. The endured evolution of AI in far off sensing guarantees to offer deeper insights into global modifications, assisting in sustainable development and useful resource control.

References

[1] Asokan, A., & Anitha, J. J. E. S. I. (2019). Change detection techniques for remote sensing applications: A survey. *Earth Science Informatics*, *12*, 143-160.

[2] Hecheltjen, A., Thonfeld, F., & Menz, G. (2014). Recent advances in remote sensing change detection–a review. *Land Use and Land Cover Mapping in Europe: Practices & Trends*, 145-178.

[3] Woodcock, C. E., Loveland, T. R., Herold, M., & Bauer, M. E. (2020). Transitioning from change detection to monitoring with remote sensing: A paradigm shift. *Remote Sensing of Environment*, *238*, 111558.

[4] Afaq, Y., & Manocha, A. (2021). Analysis on change detection techniques for remote sensing applications: A review. *Ecological Informatics*, *63*, 101310.

[5] Hussain, M., Chen, D., Cheng, A., Wei, H., & Stanley, D. (2013). Change detection from remotely sensed images: From pixel-based to object-based approaches. *ISPRS Journal of photogrammetry and remote sensing*, *80*, 91-106.

[6] Deilami, B. R., Ahmad, B. B., Saffar, M. R., & Umar, H. Z. (2015). Review of change detection techniques from remotely sensed images. *Research Journal of Applied Sciences, Engineering and Technology*, *10*(2), 221-229.

[7] Pei, H., Owari, T., Tsuyuki, S., & Zhong, Y. (2023). Application of a Novel Multiscale Global Graph Convolutional Neural Network to Improve the Accuracy of Forest Type Classification Using Aerial Photographs. *Remote Sensing*, *15*(4), 1001.

[8] Fırat, H., Asker, M. E., Bayındır, M. İ., &Hanbay, D. (2023). Hybrid 3D/2D complete inception module and convolutional neural network for hyperspectral remote sensing image classification. *Neural Processing Letters*, *55*(2), 1087-1130.

[9] Liang, G., KinTak, U., Yin, H., Liu, J., & Luo, H. (2023). Multi-scale hybrid attention graph convolution neural network for remote sensing images super-resolution. *Signal Processing*, *207*, 108954.

[10] Zhang, N., Wang, G., Wang, J., Chen, H., Liu, W., & Chen, L. (2023). All Adder Neural Networks for On-board Remote Sensing Scene Classification. *IEEE Transactions on Geoscience and Remote Sensing*.

[11] Hara, P., Piekutowska, M., & Niedbała, G. (2021). Selection of independent variables for crop yield prediction using artificial neural network models with remote sensing data. *Land*, *10*(6), 609.

[12] Ballesteros, R., Intrigliolo, D. S., Ortega, J. F., Ramírez-Cuesta, J. M., Buesa, I., & Moreno, M. A. (2020). Vineyard yield estimation by combining remote sensing, computer vision and artificial neural network techniques. *Precision Agriculture*, *21*, 1242-1262.

[13] Alam, M., Wang, J. F., Guangpei, C., Yunrong, L. V., & Chen, Y. (2021). Convolutional neural network for the semantic segmentation of remote sensing images. *Mobile Networks and Applications*, *26*, 200-215.

[14] Wang, J., Zhong, Y., Zheng, Z., Ma, A., & Zhang, L. (2020). RSNet: The search for remote sensing deep neural networks in recognition tasks. *IEEE Transactions on Geoscience and Remote Sensing*, *59*(3), 2520-2534.

[15] Boulila, W., Sellami, M., Driss, M., Al-Sarem, M., Safaei, M., & Ghaleb, F. A. (2021). RS-DCNN: A novel distributed convolutional-neural-networks based-approach for big remote-sensing image classification. *Computers and Electronics in Agriculture*, *182*, 106014.

[16] Si Salah, H., Ait-Aoudia, S., Rezgui, A., & Goldin, S. E. (2019). Change detection in urban areas from remote sensing data: A multidimensional classification scheme. *International Journal of Remote Sensing*, *40*(17), 6635-6679.

[17] Wang, X., Liu, S., Du, P., Liang, H., Xia, J., & Li, Y. (2018). Object-based change detection in urban areas from high spatial resolution images based on multiple features and ensemble learning. *Remote Sensing*, *10*(2), 276.

[18] Taneja, A., Ballan, L., &Pollefeys, M. (2015). Geometric change detection in urban environments using images. *IEEE transactions on pattern analysis and machine intelligence*, *37*(11), 2193-2206.

[19] Mertes, C. M., Schneider, A., Sulla-Menashe, D., Tatem, A. J., & Tan, B. (2015). Detecting change in urban areas at continental scales with MODIS data. *Remote Sensing of Environment*, *158*, 331-347.

[20] Hebel, M., Arens, M., & Stilla, U. (2013). Change detection in urban areas by object-based analysis and on-the-fly comparison of multi-view ALS data. ISPRS Journal of Photogrammetry and Remote Sensing, 86, 52-64.

[21] Hu, H., & Ban, Y. (2014). Unsupervised change detection in multitemporal SAR images over large urban areas. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *7*(8), 3248-3261.

[22] Teo, T. A., & Shih, T. Y. (2013). Lidar-based change detection and change-type determination in urban areas. *International journal of remote sensing*, *34*(3), 968-981.

[23] Shi, W., Zhang, M., Zhang, R., Chen, S., & Zhan, Z. (2020). Change detection based on artificial intelligence: State-of-the-art and challenges. *Remote Sensing*, *12*(10), 1688.

[24] Karantzalos, K. (2015). Recent advances on 2D and 3D change detection in urban environments from remote sensing data. *Computational Approaches for Urban Environments*, 237-272.

[25] Kwan, C. (2019). Methods and challenges using multispectral and hyperspectral images for practical change detection applications. *Information*, *10*(11), 353.

[26] Liu, S., Marinelli, D., Bruzzone, L., &Bovolo, F. (2019). A review of change detection in multitemporal hyperspectral images: Current techniques, applications, and challenges. *IEEE Geoscience and Remote Sensing Magazine*, *7*(2), 140-158.

[27] Mandal, M., &Vipparthi, S. K. (2021). An empirical review of deep learning frameworks for change detection: Model design, experimental frameworks, challenges and research needs. *IEEE Transactions on Intelligent Transportation Systems*, *23*(7), 6101-6122.

[28] Giustarini, L., Hostache, R., Matgen, P., Schumann, G. J. P., Bates, P. D., & Mason, D. C. (2012). A change detection approach to flood mapping in urban areas using TerraSAR-X. *IEEE transactions on Geoscience and Remote Sensing*, *51*(4), 2417-2430.

[29] Reba, M., & Seto, K. C. (2020). A systematic review and assessment of algorithms to detect, characterize, and monitor urban land change. *Remote sensing of environment*, *242*, 111739.

[30] Fyleris, T., Kriščiūnas, A., Gružauskas, V., Čalnerytė, D., & Barauskas, R. (2022). Urban change detection from aerial images using convolutional neural networks and transfer learning. *ISPRS International Journal of Geo-Information*, *11*(4), 246.

[31] Si Salah, H., Ait-Aoudia, S., Rezgui, A., & Goldin, S. E. (2019). Change detection in urban areas from remote sensing data: A multidimensional classification scheme. *International Journal of Remote Sensing*, *40*(17), 6635-6679.

[32] Xu, J., Luo, C., Chen, X., Wei, S., & Luo, Y. (2021). Remote sensing change detection based on multidirectional adaptive feature fusion and perceptual similarity. *Remote Sensing*, *13*(15), 3053.

[33] You, Y., Cao, J., & Zhou, W. (2020). A survey of change detection methods based on remote sensing images for multi-source and multi-objective scenarios. *Remote Sensing*, *12*(15), 2460.

[34] Chen, L., Zhang, D., Li, P., &Lv, P. (2020). Change detection of remote sensing images based on attention mechanism. *Computational Intelligence and Neuroscience*, *2020*.

[35] Si Salah, H., Goldin, S. E., Rezgui, A., Nour El Islam, B., & Ait-Aoudia, S. (2020). What is a remote sensing change detection technique? Towards a conceptual framework. *International Journal of Remote Sensing*, *41*(5), 1788-1812.

[36] Chen, H., & Shi, Z. (2020). A spatial-temporal attention-based method and a new dataset for remote sensing image change detection. Remote Sensing, 12(10), 1662.

[37] Peng, D., Zhang, Y., & Guan, H. (2019). End-to-end change detection for high resolution satellite images using improved UNet++. Remote Sensing, 11(11), 1382.

[38] Mou, L., Bruzzone, L., & Zhu, X. X. (2018). Learning spectral-spatial-temporal features via a recurrent convolutional neural network for change detection in multispectral imagery. IEEE Transactions on Geoscience and Remote Sensing, 57(2), 924-935.

[39] Alcantarilla, P. F., Stent, S., Ros, G., Arroyo, R., & Gherardi, R. (2018). Street-view change detection with deconvolutional networks. Autonomous Robots, 42, 1301-1322.

[40] Zhan, Y., Fu, K., Yan, M., Sun, X., Wang, H., & Qiu, X. (2017). Change detection based on deep siamese convolutional network for optical aerial images. *IEEE Geoscience and Remote Sensing Letters*, *14*(10), 1845-1849.