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Change detection using multispectral satellite images: a systematic review of literature

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ABSTRACT

Change detection (CD) provides information about the changes on earth's surface over a period of time. Many algorithms have been proposed over the years for effective CD of satellite imagery. This paper presents the steps to preprocess the captured satellite images, which can be used to perform predictive analysis of earth's surface by CD techniques. To design a highly effective system for CD, it is recommended that algorithm designers select efficient algorithms from any given application. Thus, this paper presents and investigates the review of most appropriate literature on CD, where CD techniques have been presented into three groups; i) thresholding, ii) clustering, and iii) deep learning. The first two categories mainly rely on the traditional machine learning, whereas the last one exploits the state-of-the-art deep learning models. At the end, the standard methods are summarized based on advantages, limitation, and research gap.

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1. INTRODUCTION

Change detection (CD) using satellite imagery is a multitemporal image processing task and it has great significance in many fields [1], [2]. A large number of applications [3], including yield prediction, crop type prediction [1], weather prediction, burned area prediction [4], can be efficiently accomplished with the help of CD, and classification systems [2]. In CD, medium, and high spatial resolution images are used since they can give more detailed change information of the larger earth's surface [5]. To get an effective CD and classification system, each block in Figure 1. must be effectively designed.

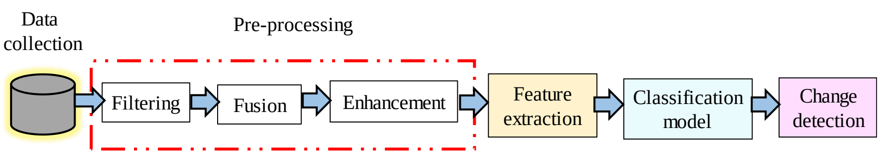

Figure 1. A typical satellite image processing system for CD

A typical satellite image processing system for CD is described as follows:

a. Data collection: images recorded by high performance satellite sensors are crisp, have several bands, and are focused on the region of interest. Images are organized by day, month, or year based on the CD application.
b. Pre-processing: in pre-processing, filtering and noise removal is performed on the captured images. In this block, first the image is checked for any noise, and then algorithms like filters [6] are applied to the images [7]. This block also performs operations like image enhancement and fusion of multiple bands or fusion algorithms [8], [9] are used, which allow the combination of multiple bands into a single image, with detailed components. Fusion reveals ground colour, texture, and shape. Image enhancing algorithms include contrast stretching, slicing, spatial filtering, and histogram equalization.
c. Feature extraction: feature extraction uses preprocessed images. This block converts images to feature vectors [10]. Algorithms like discrete wavelet transform (DWT) [11]–[13] are used for this purpose. Extracting and selecting features improves accuracy and speed. Effective feature selection reduces classification latency and delay.
d. Classification model: a high-accuracy classification model is constructed using the extracted features [14]. Algorithms like neural networks (NN) [15] and convolutional neural networks (CNN) [5], [16]–[18] are used for this purpose. This block sorts input data into N classes. This includes crop identification and weather classification.
e. CD: this block evaluates temporal data from different classification instances in order to approximate CD. After getting the CD map, post-processing can be applied to make it more accurate. Improving these blocks' efficiency will improve the ultimate system's efficiency. Many methods have been proposed for this purpose. The next part discusses how to incorporate these algorithms to increase system efficiency.

2. REVIEW OF TECHNIQUES

Using satellite imagery to detect changes in field-specific features requires image and signal processing methods. CD techniques vary. The difference images (DI)-based technique is the most studied. We consider the two images that are obtained from the same location at different instants, T_1 and T_2 [7]. First, DI is created using T_1 and T_2 satellite images. Then, DI is thresholded and clustered. Thresholding uses DI's change map (CM). First, we extract features from DI, then we apply them to clustering to get a CM. The following are both CD methods.

2.1. DI-based synthetic aperture radar images CD techniques

DI is produced using difference and ratio operators. The difference operator is effective for optical satellite images but not synthetic aperture radar (SAR) images and it doesn't reduce speckle noise. The ratio operator generates SAR Dis [7]. Besides this, polarimetric change vectors (PCVs) have also been explored to improve CD performance in SAR imagery. PCVs with magnitude and directional images are proposed in [19] for binary and multiclass CD. Geetha and Kalaivani [20], Laplacian pyramid (LP) uses multiscale representation and thresholding, while CAD lowers speckle noise and feature broadening. The LP maintains speckle-free images and DI. This technique has been tested on simulated and actual SAR image databases for disaster management. Besides this, in [21], iterative Otsu thresholding is recommended for DI segmentation. This iterative Otsu technique reduce speckle noise. This approach improves large-object segmentation.

2.2. Thresholding-based CD technique

Thresholding-based methods were used to obtain the final CM in CD [22]. Selecting the proper threshold for segmentation is the main requirement for the threshold-based CD techniques. To make the threshold selection procedure significant the number of changes should be significant in the thresholding-based methods [23]. Setting up of strict detection threshold is necessary to avoid false alarms. Prior knowledge of the scene will lead to best threshold level selection. The new DI is obtained from the original images by using the thresholding models [24]. The various existing methods using threshold-based CD.

Yang *et al.* [25] have presented a feature learning network in deep pyramid for multiscale CD. For CD a deep pyramid feature learning network (DPFL-net) was used. It was an unsupervised CD method by which unchanged areas and pyramid features were updated alternatively. Experiment was conducted in two homogeneous datasets such as farmland and Mexico and four heterogeneous datasets such as river, Shuguang, Texas and California. In the learned features and spatial details, it contains more sematic meaning and contextual information. The CD map was obtained by using Otsu's thresholding method. To aggregate multiple different scaled DI, the fusion block was used which gives a strong separable and low noise DI. The pyramid's feature constrain process was constrained by using local consistency. Lei *et al.* [22] have presented a heterogeneous remote sensing (RS) CD based on adaptive local structure consistency (ALSC). Consistency between the local structure of two images was constructed using an ALSC based CD method. To evaluate this method sardinia dataset, shuguang dataset, Wuhan dataset and California datasets were used. It was an unsupervised method. The final CM was obtained by using Otsu thresholding method. Zhang *et al.* [23] have presented a histogram fitting error minimization (HFEM) based unsupervised SAR image CD for few changed areas. HFEM was an unsupervised thresholding method. Four real SAR datasets and a synthetic dataset was used. The lack of pixel level CD was overcome by using half-normal conditional random field (HNCNF) which was a spatial analysis method which combines neighborhood information. Gupta *et al.* [26] have presented a local neighborhood information-based CD in Landsat images. The threshold for each pixel position was calculated using the local information using Novel CD technique based on local neighborhood information. Based on the inter image and inter block information the threshold was calculated using the Otsu's thresholding method. Jiang *et al.* [27] have presented a Siamese semi supervised network in heterogeneous RS images for efficient CD. A transfer learning-based semi supervised Siamese network (S^3N) was used to reduce high computation cost. To obtain the final binary map of CD Otsu thresholding method was used. To validate the S^3N prevent panchromatic image, post-event SAR image and ground truth datasets were used. Sun *et al.* [28] have presented an unsupervised image regression based on sparse constrained adaptive structure consistency for heterogeneous RS CD. Adaptive probabilistic graph (APG) was constructed by dividing multitemporal images into pixels by using the image regression method based on sparse constrained adaptive structure consistency (SCASC). To compute the binary CM Markov random field (MRF) was used which combines the spatial contextual information and change information. The segmentation was done by using the Otsu thresholding method. Goswami *et al.* [29] have presented a CD by comparing the RS image data of machine learning and algebraic methods. Two CD techniques were used for detecting change they are the separability matrix and the image differencing CD technique. The threshold was chosen by using the corner method. The input images were taken from the Landsat dataset. Li *et al.* [24] have presented a CNN-based CD from SAR images guided by saliency enhancement. By using SAR image accuracy of CD was improved. The automatic threshold Otsu model was used to threshold the saliency map's small noise regions in the image and was removed. For classification a hierarchical fuzzy c-means (FCM) model was used. To create the final CM convolutional-wavelet networks were used. Table 1 summarizes various existing methods for thresholding-based CD methods and also summarizes advantage, limitation, and research gap.

Table 1. Description of various existing methods for thresholding-based CD methods

Author	Method	Advantage	Limitation	Research gap
Yang *et al.* [25]	DPFL-net	In both heterogeneous and homogeneous cases DPFL-net method was more effective for CD.	If DPFL-net was not pretrained the feature transformation was difficult which leads to degradation in the overall performance.	Need to improve the initialized probability map's efficiency and extract the objects deep features.
Lei *et al*. [22]	ALSC based CD method	In different heterogenous datasets this method achieves effective performance. Heterogeneous data confusions were avoided.	Computational burden was increased.	Need to reduce the computation burden.
Zhang *et al*. [23]	HFEM, HNCNF	Too much of noise in the image will not affect the segmentation result by using HFEM.	If there was large number of changes other thresholding methods perform better then HFEM.	Need to explore some nonlinear change features based novel CD frameworks such as Kullback Leibler divergence (KLD) and mean shift information theoretic CD (MS-ITCD).
Gupta *et al.* [26]	Novel CD technique based on local neighborhood information	Reduces false alarm. False detection was reduced. Accuracy was improved. Performs better against noise.	With increase in patch size increase in number of changed pixel leads to false detection.	Need to upgrade this method for better performance in CD.
Jiang *et al.* [27]	S^3N	Reduce the computational cost. The effectiveness and efficiency were validated using S^3N. Increase in detection performance.	When the number of training samples increased execution time will also increased.	The time efficiency of S^3N need to improve for small size input images.
Sun *et al*. [28]	SCASC based image regression method	The accuracy of segmentation model was improved. Detection performance was improved.	The regression result of gradient sparsity of DI needs to be improved.	There was a need to investigate the distribution model of DI to design an accurate segmentation model.
Goswami *et al*. [29]	CD based on post classification comparison	Compared with algebraic technique post classification method's accuracy was reliable.	The decision tree-based technique was an old technique. Time analysis was not performed. Only limited dataset was used.	Instead of using decision tree-based classification algorithm there was a need to use other classification algorithms. Need to consider spatial information.
Li *et al*. [24]	SAR image CD algorithm	Enhanced the accuracy of the CD.	The clustering method and the saliency detection methods used were not an end to end deep learning model.	Need to construct an end to end convolutional wavelet neural network (CWNN) model for CD.

2.3. Clustering-based CD techniques

Grouping the similar objects into a set of objects is termed as clusters [30]. The changed and unchanged position on the difference map was extracted using the clustering techniques [31]. To generate the super pixels clustering techniques were used [32]. Pseudo training samples were randomly selected from two changed and unchanged regions in kernel-based clustering techniques [33]. The clustering algorithms are used to find the final CM from the features obtained from the feature extraction [34]. The input data to the clustering technique influence the clustering result [35]. The various existing methods using clustering-based CD.

Zheng *et al*. [32] have presented an unsupervised CD by difference learning based on cross-resolution. In preprocessing step unsupervised CD was done on different resolution images without resizing the image by using cross resolution difference learning. This method was experimented using the Yanming lake dataset, Hongqi canal dataset, Weihe river dataset and Yandu village dataset. Simple linear iterative clustering (SLIC) technique was used for image segmentation. Liu *et al*. [31] have presented an unsupervised CD (USCD) of image translation based heterogeneous data. USCD method was used to detect the changes in the heterogeneous RS images. Gloucester dataset, Shuguang dataset, Sardinia dataset, and Wuhan dataset were used to experiment USCD method. The postevent optical image was obtained from preevent image by using CycleGAN technology. K-means clustering technique was used for clustering. Qu *et al*. [36] have presented CD using a dual-domain network in synthetic aperture radar images. In SAR CD in order to exploit the frequency and spatial features dual domain network (DDNet) was used. To classify the DI into three clusters a hierarchical FCM clustering technique was used. The center region of each patch was emphasized by using multi region convolution (MRC) module. Ottawa dataset, Sulzberger dataset and yellow river dataset were used to demonstrate the DDNet. Gupta *et al.* [33] have presented a CD in Landsat images using RBF-based clustering and unsupervised learning. To provide the discriminant features an orthogonal unsupervised discriminant projection (OUDP) was used. For better clustering a novel radial basis function-based clustering was used. These methods were experimented in multitemporal datasets obtained from Landsat satellite. Gupta and Ari [30] have presented a satellite image CD based on spatial neighborhood mutual information (SNMI). SNMI K-means (SNMIKM) algorithm was used to detect the unchanged pixels. The SNMIKM fails to detect changed pixels due to overlapping clusters therefore SNMIFCM algorithm was used to perform clustering in overlapping clusters. Gupta *et al.* [34] have presented an unsupervised CD based on feature fusion in optical satellite images. The features were extracted using canonical correlation analysis (CCA) techniques and Gabor wavelet kernel technique. For unsupervised CD a feature fusion technique was used in which serial fusion strategy was used. to generate the binary map a FCM algorithm was used for clustering. This method was experimented using the multitemporal images captured by Landsat 5 and 7.

Liu *et al*. [37] have presented a CD using object-based image analysis with deep learning approach. A CNN end to end learning architecture with object-based CD was used to detect the change in the image. With K-means algorithm an unsupervised clustering classification was performed in the extracted features. This method was tested in the satellite images with very high resolution from the federal emergency management agency (FEMA). To check the method's CD capability in natural disasters a real-world application was used. Zhang *et al*. [35] have presented a CD and river ice monitoring technique with SAR and multispectral images. Sparse reconstruction-based channel extraction method (CE-SR) was used to detect timing and amount of river ice distribution. To detect the river ice region accurately in the SAR images the adaptive threshold segmentation method was used. To differentiate ice, water and shore FCM clustering technique was used. Ice coverage of yellow river was detected by analyzing the data from Canadian space agency (CSA) RADARSAT1 and Landsat 7 TM sensor images. Dong *et al*. [38] have presented a deep clustering self-attention multiscale technique in SAR images for CD. In the view of unsupervised deep clustering combining deep convolution model with K-means ++ clustering provides a new access to the change. To evaluate this method images from yellow river dataset, De gaulle airport image pairs and red river image pairs were used. Table 2 summarizes various existing methods for clustering-based CD methods and also summarizes advantage, limitation, and research gap.

2.4. Deep learning-based CD techniques

Deep learning is used as the feature extractor or backbone to resolve vision problems because of their good generalizability [39] and is significant for solving the problem of a large amount of data redundancy [8]. These methods have essential applications in CD [40], RS image classification [8], and visual recognition tasks [40]. In several disciplines, deep learning models have been effectively used, including image classification, natural language processing, and voice recognition [41]. Some innovative deep learning techniques usually exploit certain spatial features as support to increase accuracy [8]. All the deep learning-based CD models are discussed further with respect to published techniques.

Table 2. Description of various existing methods for clustering-based CD methods

Author	Method	Advantage	Limitation	Research gap
Zheng *et al.* [32]	Cross-resolution difference learning method	Since no resizing of the input image was needed this method achieves better performance. Achieves more accurate CM.	Newley built roads were misclassified. Difficult to detect too small areas.	Needs to check CD multitemporal images with different resolution.
Liu *et al.* [31]	USCD based on image translation	Detection accuracy was improved. Good performance in the CM.	The detection results were not much reliable.	For heterogeneous RS images new techniques were needed to improve the generated images quality to achieve better performance in CD.
Qu *et al.* [36]	DDNet and MRC	Speckle noise was efficiently suppressed. Classification performance was improved.	The computational burden increases with the larger patch size.	To verify DDNet there was a need to work on large scale dataset.
Gupta *et al.* [33]	OUDP	Achieves better classification. Detects maximum changed regions. Generate noise free result.	Increase false alarm. Homogeneity decreases with increase in patch size.	Need to improve the method to reduce the false alarm.
Guptha *et al.* [30]	SNMIKM, SNMIFCM	Accuracy was increased. Performance was better for datasets with different patch size. Reduce false alarms.	Some parts of changed areas are not detected in the visual result.	Need to improve the system to get better visual results.
Gupta *et al.* [34]	Feature fusion based unsupervised CD	Less total error. Detect changes more accurately with less noise and false alarms.	The overall accuracy was not much changed by reducing the feature dimension.	Need to improve the overall accuracy of the method.
Liu *et al.* [37]	OBIA, Object based CD method	Overall accuracy of the CD was improved. Good performance in computational efficiency.	To make this method practical there was a need to improve the generalization.	Investigation needed for the feature fusion methods, feature representation and analysis unit to know how they impacted the CD model's generalization power.
Zhang *et al.* [35]	CE-SR	Achieves more accurate channel extraction. For multi temporal and multi sensor RS images this method achieves good performance.	There was a need of accurate threshold.	Need to implement deep neural network-based learning method for CD in multi sensor and multi temporal images.
Dong *et al.* [38]	Difference representation learning framework	In real SAR datasets the unsupervised CD's performance improved with different resolutions. Achieves the state-of-the-art result.	The KM++ and the network was initialized randomly leads to effect in stability of the method. The performance of the system degraded if the number of epochs greater than 50.	Good initial parameters with suitable network architecture were needed.

2.4.1. Convolutional neural network

CNN is a class of artificial neural network in deep learning. CNN classifiers were used to obtain the CM of the RS images [42]. It effectively detects the changes in the RS images. CNN based models were affected by higher computational complexity and long-range contextual information loss. To overcome this multiscale context aggregation with CNN network (MSCANet) was used. MSCANet method was experimented using the HRSCD dataset and CLCD dataset. Using transformers in CD generate a global perception capability. But use of transformers in CD leads to increase in resource consumption. To overcome this CNN with transformer and asymmetric cross attention hierarchical network (ACAHNet) was used which reduce the computational complexity [43]. The local sensing capability of the CNN was combined with the global attention of the transformer to eliminate the effects in pseudo changes. ACAHNet was experimented using three public datasets such as SYSU-CD, LEVIR-CD, and CDD.

2.4.2. U-Net

Semi-supervised learning uses a two-step technique that combines feature maps with semantic information and also combines representation learning and binary cross-entropy. This approach lessens the impact of limited data by employing a U-Net like structure to extract representative and generalized characteristics [14]. Figure 2 shows U-Net model. U-Net model has convolution and maximum pooling like CNN. It also provides skip connections between the down-sampling and up-sampling paths and a concatenation operator.

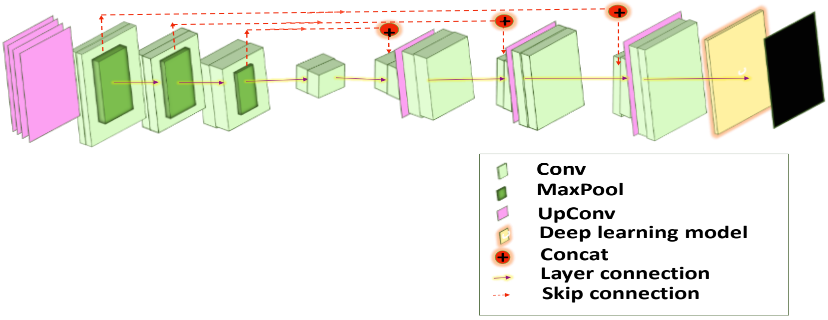

Figure 2. U-Net with deep learning model

U-Net is a semantic segmentation architecture. To efficiently produce the multiscale change features the differential map of two input images was given as input to the U-Net [5]. At different scales the detection result was predicted using multiple side output fusion (MSOF) module. The DIfUnet++ was experimented using the LEVIR-CD dataset. An unsampling method called Dupsampling was used for the accurate detection of the detail edges. The feature map develops latent noise problem which was overcomes by using U-Net based Siamese network [44]. Based on the pretrained encoder the CD network was trained by using the supervised contrastive pretraining and fine-tuning CD (SCPFCD). SCPFCD method was experimented using the semantic CD dataset, season varying dataset and WHU building dataset. To obtain the final CM the images goes through several intermediate processing steps results in error accumulation problem [45]. To overcome this accumulation problem U-Net++ based on encoder decoder architecture was used in which highly accurate CM was generated using both fine grained and global information. At different scales global information was obtained using the U-Net. SNUNet was effective but the error was significantly increased in the complex ground object information [46]. This method was tested using the DSIFN-CD, SYSUCD, and WHU-CD datasets.

2.4.3. Siamese network

Siamese network obtains the changed area by identifying the image pairs by extracting features from the input image pairs [47]. The deep Siamese networks extract features by sharing weights and uses distance pairs to measure the similarity of feature pairs. The Siamese network generate the CM by using a simple threshold segmentation on the distance metric. Between the bitemporal images the spatial temporal relationship was captured using Siamese network and was mapped for comparison into the feature space [48]. Features were extracted from the image pairs and the CM was obtained from these image pairs by using the Siamese network-based method [47]. The deep Siamese network extract features by sharing weights and the CM was generated using the threshold method. The raw image pair was inputted to the fully convolutional Siamese network to generate the feature pair. Siamese network with focal contrastive loss (FCL) was used to improve the performance of the change information. To achieve an accurate pixelwise CD a bilateral semantic fusion Siamese network (BSFNet) was used [48]. The deep and shallow sematic features was extracted using two subnetworks and the feature fusion and sematic description optimization was done by using BSFNet. The problems faced due to complex environment was achieved using BSFNet method.

2.4.4. Generative adversarial network

The generative adversarial network (GAN) was used in computer vision for editing the image attributes [49]. The GAN process consists of two parts they are discriminator and generator. The generator generates images and the discriminator judges the images and set it as true or false. This method can be easily implemented [50]. The better co registered map was generated by using GAN. Li *et al.* [51] have presented a CD network based on deep translation GAN for SAR RS and optical images. GAN was mostly used in image attribute editing and image style migration which consists of two parts such as discriminator and generator. The images from one domain were mapped to another domain into the same feature space through a cyclic structure using deep translation based CD network (DTCDN). The method was tested using four datasets from Glouster, California, and Shuguang village datasets. The method was tested using four datasets from Glouster, California, and Shuguang village datasets. The better co registered map was generated by using GAN [52]. To align features and to obtain pixelwise representations from the shifted image pairs a Siamese pseudo network was used. Two heterogeneous images were translated to a single domain by using the conditional GAN. Radoi [50] have presented a multimodal CD under CutMix transformations on GANs. To achieve the unsupervised multimodal CD image translation GAN based modality to modality (M2M) translation was used. The image was trained using CutMix transformation. To determine the prior change information in images K nearest neighbor (KNN) was used. This method was tested using Sardinia, Toulouse, China, UK, and California datasets.

2.4.5. Recurrent neural network

To deal with sequence data recurrent neural network (RNN) was used [52]. The prediction map generated by the RNN model gives better spatial variations which enhances the prediction accuracy. In different seasons RNN models shows stable accuracy. The final CM with fine edges was generated by using the RNN model [53]. Long short-term memory (LSTM) with deep RNN and gated recurrent units (GRU) was used to predict historical observations based short term vegetation index (VI) [50]. The pixel based FGRU and FCLSTM and the patch based ConvGRU and ConvLSTM was used. Different growing seasons and different vegetation types was stably analyzed by using the RNN based methods. NDVI and MODIS datasets were used to train this method. In different seasons RNN based methods gives stable accuracy. The removal of distance noise and the edges of the changed areas was refined using the conditional random field RNN (CRF-RNN) thereby improves the overall performance [53]. The knowledge of pairwise potential and unary potential was integrated to improve the CD using the CRF-RNN. LEVIR-CD and SZTAKI air change benchmark datasets were used to train this method.

2.4.6. Auto encoder

Classic auto encoder consists of encoder and decoder [54]. Stack of convolutional and deconvolutional layers were present in the encoder and decoder respectively. The features that are extracted was considered as the global feature if the auto encoder was fully connected and applied directly in processing images. Wu *et al*. [55] have presented a commonality autoencoder for CD from heterogeneous images to learn common features. Commonality autoencoder CD (CACD) an unsupervised method was used to compare the heterogeneous images. This method was experimented using yellow river data set, Sardinia dataset, Shuguang village dataset, Stonegate dataset, and the river data set. This method was experimented using yellow river dataset, Sardinia dataset, Shugung village dataset, Stonegate dataset, and the river dataset. The intrinsic relationship of two images explored using a dual auto encoder (COAE). The difference map was classified using a segmentation algorithm called fuzzy local information c means clustering (FLICM) algorithm. To experiment this method images acquired from yellow river estuary, Sardinia, Shuguang, Taiwan, Terra SAR datasets were used. Autoencoder was an unsupervised deep learning network and was a powerful feature extraction technique that extract features from the unlabeled data [56]. Autoencoder consists of an encoder and decoder. The encoder will extract the information from the input and the decoder reconstruct the input. The selective adversarial adaption CD technique using auto encoder was evaluated using yellow river, Sardinia, De Gaulle airport, Ottawa, and Mexico datasets. Table 3 [5], [42]-[47], [50], [52]-[55], [57], [58] (see in Appendix) summarizes various existing methods for for deep learning-based CD methods and also summarizes advantage, limitation, and research gap.

3. DISCUSSION AND SUMMARY

All of the architectures are included to show the variety of algorithms are as follows:

a. Variety of architectures: the inclusion of architectures such as GRU, AE, S^3N, and LSTM-based algorithms showcases the breadth of approaches utilized in CD. Each architecture brings its own set of advantages and is tailored to specific requirements and constraints of the task at hand.
b. CNN variant architectures: beyond the aforementioned architectures, various CNN variants are proposed in literature, such as CWNN, deep CVA, and self-paced learning architectures. These variants offer different methodologies for feature extraction, representation learning, and classification, contributing to the overall diversity of CD techniques.
c. Complex architectures: the mention of complex architectures incorporating Markov chains, spectral unmixing, regression-based learning, and decision fusion highlights the integration of multiple techniques to enhance CD performance. These architectures enable the assembly of CNNs for multi-algorithmic applications, leveraging the strengths of different methodologies for improved accuracy and robustness.
d. Performance comparison with linear methods: it’s noted that CNN and its variants outperform traditional linear classification methods like SVM, PCA, and Markov models. This underscores the effectiveness of deep learning approaches in handling complex data distributions and capturing intricate patterns present in CD tasks.
e. Enhancements through cross-domain and transfer learning: cross-domain and transfer learning techniques are identified as means to improve CNN accuracy. By leveraging knowledge from related domains or pre-

trained models, CNNs can adapt to new tasks more efficiently, enhancing their generalization capabilities and performance in diverse settings.

f. Role of generative and selective adversarial networks: generative and selective adversarial networks play a crucial role in improving transfer learning, particularly in real-time applications like field CD, and ice melting detection. These networks enable the generation of realistic data samples and facilitate domain adaptation, addressing challenges associated with domain shift and limited labeled data.

All of the architectures are included to show the variety of GRU, AE, S^3N, and LSTM-based algorithms. Other CNN variants architectures are proposed in [1], [27], [50], [59], [60] which use CWNN, deep CVA, and self-paced learning, respectively. In addition, complex architectures that use Markov chains, spectral unmixing, regression-based learning, and decision fusion are mentioned in [61]. These secondary methods can be used to assemble CNNs for multi-algorithmic applications. CNN and its variants outperform linear classification methods like SVM, PCA, and Markov models. Cross-domain and transfer learning improve CNN's accuracy. Generative and selective adversarial networks improve transfer learning, making them useful for real-time applications like cover CD, field CD, and ice melting detection. In order to evaluate the performance of the CD algorithms, this section reviews the metrics, viz., precision (P), recall (R), accuracy (A), and F1-measure (F1) [51], [62]. Most of the CD studies consider all the parameters as an achievement measure.

4. CONCLUSION

This paper has addressed the review of recent CD techniques. As the topic is broad and instant time, a complete analysis is impossible. We focused on deep learning techniques for CD, which are trending. We've covered popular methods and new innovations. The CD organizes techniques into three categories: thresholding, clustering, and deep learning are three methods. Deep learning algorithms detect changes in satellite images better than thresholding and clustering. Deep learning networks perform well in cloudy and rainy satellite images. CD algorithms have developed due to the advent of CNN. Precision, recall, accuracy, and F1-measure values are easily achieved using these methods. Applications like farms, rivers, and ice cover, that require CD algorithms have higher accuracy with CNN variants. The improved results in parameters increase the network's computational overheads. These approaches have enormous computational overheads since they aim to cover a large number of identical feature vectors to enhance performance. Satellite images are used to evaluate earth's surface. The types of RS data selected for analysis depend on the project's goals and the area's data. As a final observation, we point out that all the techniques have advantages, limitation and research gap. It is not possible to select any particular technique that could be the best. Depending on the various applications from the end-users, existing techniques can be improved further. The following future prospects must be considered in the field of CD; i) design of effective feature selection methods, which must be embedded into CNN architectures for reduced complexity and high-speed CD applications and ii) cross-domain CD using machine learning for intelligent feature selection and hyperparameter tuning is needed to improve current methods' performance and applicability to larger databases.

APPENDIX

Table 3. Description of various existing methods for deep learning-based CD methods

Author	Method	Advantage	Limitation	Research gap
Liu *et al.* [42]	CNN transformer network with MSCANet	State of the art CD performance was achieved. False alarm reduction and boundary extraction was achieved. Low computational complexity.	During model training there was a need to learn the number of parameters.	Need to reduce the space complexity.
Zhang *et al.* [43]	ACAHNet	Computation resource consumption was low. Comprehensive performance was high.	Increase in computation complexity. Number of parameters was high.	Improve the system with less storage and computation cost.
Zhang *et al.* [5]	DifUnet++	Powerful to irrelevant visual differences. Performs better than state of art methods.	Training images of large size was time consuming.	Enhanced DifUnett++ was needed for better CD.
Wang *et al.* [44]	SCPFCD	Landcover's Interclass uniformity and interclass distance was increased thereby increase CD performance.	To construct the sample pairs the CD label information was not fully utilized by land contrastive learning.	For supervised pretraining Reconstructing a masked image need to be explored for bitemporal images.
Peng *et al.* [45]	U-Net++	Generate final CM with high accuracy.	Lot of true CM's were required	Need to improve sample generation techniques and supervised learning

Table 3. Description of various existing methods for deep learning-based CD methods (continue)

Author	Method	Advantage	Limitation	Research gap
Zhao *et al*. [46]	Feature interaction and multitask learning (FMCD)	Improved detection ability in complex scene. Interference of shadow and other factors were reduced.	Obtaining reconstructed images with high quality was difficult.	Need to enhance the system to get high quality output.
Wang *et al*. [47]	Focal contrastive loss network (FCLNet)	Achieve better result in focus learning and class imbalance.	CM cannot distinguish the changed buildings.	Need to generate finely CMs.
Chen and Bruzzone [57]	Pixel wise self supervised learning (PixSSL)	Obtained better CM on water and vegetation areas. Low computational cost.	Long time image series was not handled. Unable to handle the change types classification.	Need to map the change types correspondingly by tracking the changes between the time series images.
Radoi [50]	M2M with CutMix	The overall accuracy of the system was increased.	Pre training was needed for the CutMix transformation.	Updating this model will be used for multimodal time series analysis.
Yu *et al*. [52]	FCGRU, FCLSTM, ConvGRU, and ConvLSTM	Less computation cost. Sufficient prediction accuracy was provided.	It was harder to tune and configure ConvGRU and ConvLSTM.	Need to extend this method with multisource data.
Zhan *et al*. [58]	Bilinear CNN (BCNNs) and object based change analysis.	Land surface changes were identified with less noise. Achieved better detection performance.	Small changed regions were not detected properly.	For different sensors need to identify changes between the multitemporal RS images.
Hu *et al*. [54]	Autoencoder Anomaly CD (ACDA)	Noise of the final result was reduced. Time consumption was low.	The intensity value will be low if there was no anomaly change.	Combining spatial and spectral features needs more attentions for background changes in complex space variant.
Zheng *et al*. [53]	CRF-RNN	Less number of parameters with advanced capabilities. Improves error identification. Removes distance noise.	Training time was high.	Need to be improve learnable pairwise potential networks over smooth effects.
Wu *et al*. [55]	CACD	CACD achieves better quality for the complex textures like mountains. CACD was not sensitive to noise.	The small changed regions CD performance decreased with the increase in patch size.	The ideas of COAE need to apply to explore the CD of the images with changed region larger than the unchanged region.

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