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Analysis on change detection techniques for remote sensing applications: A review

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ABSTRACT

Satellite images taken on the earth's surface are analyzed to identify the spatial and temporal changes that have occurred naturally or manmade. Real-time prediction of change provides an understanding related to the land cover, environmental changes, habitat fragmentation, coastal alteration, urban sprawl, etc. In the current study, various digital change detection approaches and their constituent methods are presented. It was found that (i) change vector analysis method provides better accuracy among the algebra-based change detection approach, (ii) discrete wavelet transformation is better among transformation techniques, (iii) considering the artificial neural network and fuzzy-based approaches to analyze the prediction performance over the traditional state-of-the-art approaches, (iv) analyzing the promising outcomes generated by deep learning techniques for difference analysis related to the images captured at a different instance of time. The brief outlines of different change detection approaches are discussed in this study and addressed the need for improvement in the methods that are developed for the detection of a change in the remote sensing community.

1. Introduction

Over the past few years, a significant number of earth-monitoring satellites has been deploying by space agencies. End users are flooding with an enormous variety of imagery such as infrared vs Synthetic Aperture Radar (SAR), high-resolution vs broad-coverage, mono vs multispectral, often in a periodic time sequence. Satellite imagery has been effectively implementing in classification, change detection, feature extraction, and many other applications. However, concerning change detection and classification, remote sensing imagery processing includes a few preprocessing processes. Besides, it is majorly dependent on the techniques that have been applied (Mountrakis et al., 2011). Lately, deep learning techniques have been successful not only in classical issues like voice recognition, detection, recognition, and text segmentation but also in much other real-world application (Bengio et al., 2013, Lecun et al., 2015; Hinton and Salakhutdinov, 2006; Hu et al., 2015; 2013 | MIT Technology Review [WWW Document], 2021). The deep learning techniques are influenced by the structure of the brain which is considered as a profound architecture of human visual systems and the perceptron's are expressing several absorption phases (Li et al., 2018).

Change detection is characterizing as the mechanism by which a feature or phenomenon is identified by analyzing it at its distinctive period. Due to natural or human-made occurrences, detection of a change is a process of detecting geospatial changes from Geographical Information system (GIS) data (Manakos and Lavender, 2014). Change detection is of great significance to detect satellite mapping changes, observing environmental changes, and Land use and Land cover (Lu-Lc). Remote sensing satellite collects satellite images at different resolutions and uses them to detect changes (Asokan and Anitha, 2019). The remote sensing techniques are utilized to monitor and analyze environmental issues at the global, national, and regional level. The purpose of change detection is to analyze the variability in the images related to a specific area that is captured over a distinct period of times. Multi feature-based fusion techniques are utilized for the detection of changes in Landsat images with three bands that are Red, Green, and Blue (RGB) (Cai et al., 2018). The method of change detection is commonly used for tracking environmental conditions such as the impact of natural disasters and urban expansion, finding changes in vegetation, evaluating desertification, and detecting specific urban or natural variations in the

Abbreviations: Lu-Lc, Land use and Land cover; RS, Remote sensing; CD, Change Detection; AE, Auto-encoder; VHR, Very High Resolution; CNN, Convolutional Neural Network; GIS, Graphical Information System; DL, Deep Learning; AI, Artificial Intelligence.

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Table 1
List of studies and their dataset.

Authors	Year	Dataset	Location	No. of images	Resolution	bands
(Zanchetta et al., 2016)	2016	LANDSAT	AZRAQ OASIS	42,992	2634 × 3126	7 BANDS
(Singh and Singh, 2017a)	2017	LANDSAT	JAMMU & KASHMIR	256	–	7 bands
(Johnson et al., 2017)	2017	LANDSAT	PHILIPPINES	108	4500 × 4500	3 bands
(Pandey and Khare, 2017)	2017	LANDSAT	UPPER NARMADA BASIN (UNB)	–	931 × 644	4 bands
(Luo et al., 2016)	2016	LANDSAT	–	5000	1024 × 614	3 bands
(Luo et al., 2018)	2018		HANYANG		3000 × 3000	–
(Suresh and Lal, 2017)	2017	LANDSAT		–	1464 × 1163	
(Hagag et al., 2017)	2017	LANDSAT	–	4000	677 × 512	3 bands
(Haque and Basak, 2017)	2017	LANDSAT	BANGLADESH	–	938 × 528	4 bands
(Ochege et al., 2017)	2017	LANDSAT	NIGERIA		938 × 528	4 bands
(Wang et al., 2018a)	2018	LANDSAT	ANHUI PROVINCE, CHINA	853	1669 × 1368	3 bands
(Wang et al., 2018c)	2018	LANDSAT	NORTH XINJIANG, CHINA	853	1426 × 1426	3 bands
(Pradhan et al., 2018)	2018	LANDSAT		48,828	256 × 256	–

environment (Singh, 1989). Change identification due to repeated coverage at short intervals and reliable image quality is one of the primary features of remotely sensed data collected from Earth-orbiting satellites (Anderson, 1977; Ingram et al., 1981; Nelson, 1983; Singh, 1984). Techniques for change detection executing in different ways, like Lu-Lc (Liu et al., 2018a; Liu et al., 2018a, 2018b, 2018c, 2018d; Amici et al., 2017), Deforestation, settlement in urban areas, and natural disaster change (Feizizadeh et al., 2017; Hölbling et al., 2015; Kleynhans et al., 2015). Remote Sensing (RS) technology has proved to be the essential data source for continuous observation and evaluation over time.

1.1. Need and importance of change detection

Improving the Remote sensing (RS) imaging framework and the approachability of Very High Resolution (VHR) satellite images has made life modest. It helps researchers to categorize the objects for remote sensing applications that have traditionally been handled by field surveys. One of the key features of real-time remote sensing satellite imagery is that we can analyze climate change accurately. The value of identifying change helps to understand human interactions with the environment that can contribute to decision-making for growth concerning a specific area. The decision of change is entirely based on the application for which the detection of the change is used. The detection of changes applied to real-time applications is highly problematic because, it requires various processing steps, such as identifying a problem with the detection of changes, preprocessing the image, and evaluating the application-specific algorithm.

Nowadays, VHR satellite images are available for providing clear information about the earth for the detection of changes and constantly plays a crucial role in the field of remote sensing. Especially, with the continuous enhancement of the resolution in satellite images, the problem is further increased to design an appropriate approach for the detection of changes from VHR images. Table 1 provides a brief survey on change detection using Landsat data with different resolutions. (See Tables 2–5.)

Although the change detection techniques are applied in several different fields, only a few methods are followed by the researchers. The purpose of these approaches is to determine the substantial changes with respect to a specific area from the images. Fig. 1 illustrates the flow for the detection of changes from satellite imagery. It has been realized that the presence of noise and artifacts in original images influencing the detection accuracy. Moreover, the selection of a Change detection (CD) technique also affects the performance of the detection. This study aims to explore several change detection techniques implemented in remote

Table 2
Analysis of different studies on Algebra-based Change detection approaches.

Authors	CD Approaches	Images	Area	Accuracy
(Ke et al., 2018)	Image Differencing	Multispectral Images	China	0.9451
(Luppino et al., 2019; Ridd and Liu, 1998)	Image regression	Heterogeneous Images	–	–
Liu et al., 2015	CVA (change vector analysis and Image Rationing	Multi-temporal HS Images	California	0.99
(Ferraris et al., 2017)	Fusion Based approach	Multispectral and hyperspectral (HR and LR) LANDSAT 8	USA	0.97
Xiong et al., 2012	Image Rationing	SAR Images	China	–
Barber, 2015	Generalized Likelihood ratio test (GLTR)	SAR Images	–	–
He et al., 2014	Dynamic thresholding	Multispectral images	Alaska	0.94
Qi et al., 2015a, 2015b	CVA	PolSAR	Panyu china	0.99

Table 3
Different studies on Transformation based Change detection approaches.

Authors	CD Approaches	Images	Area	Accuracy
Sadeghi et al., 2016	PCA (Principal Component Analysis)	Landsat-TM_4	Islami Island (Urmia Lake, Iran)	0.96
Massarelli, 2018	Tasseled Cap Transformation	Landsat Images	Brindisi	0.91
Thakkar et al., 2016	Tasseled Cap Transformation	IRS 1C LISS-III image Landsat 5 –TM Landsat 8-OLI SR	India	0.84
(Vázquez-Jiménez et al., 2017)	Chi-square	Quickbird, WorldView, GeoEye images	Guerrero Mexico	–
Solano-Correa et al., 2018	Tasseled Cap Transformation	Heterogeneous Images (SAR and optical)	Trentino Italy	–
(Liu et al., 2018c)	Discrete Wavelet Transform (DWT)	Quickbird Images	UK	0.96
(Zhuang et al., 2017b)	Discrete Wavelet Transform	USACE, NOVA 2.1 small UASS	Yanzhou, China	–
Liu et al., 2018a, b, c, d	Discrete Wavelet Transform (DWT)	SAR Images	Ranch, Florida	0.87
Liu et al., 2016	Discrete Wavelet Transform (DWT)	Radaesat −2 Lansat 7	–	0.99

Table 4
Detailed Survey on classification-based change detection.

Authors	CD approach	Images	Area	Accuracy
Raja et al., 2013	Wavelet-Based Post Classification	IRS-1B and IRS-P6	Madura city couth India	0.82
Gong et al., 2015	Deep learning	SAR	Ottawa	0.98
Alonso-Montesinos et al., 2016	Bayesian network classifier	Cloud images	–	0.97
Singh and Singh, 2017a,b	Genetic algorithm trained radial basis function neural network	SAR	Ottawa	0.85
Liu et al., 2016	Deep neural network	Heterogeneous optical and Radar images	China Mexico	0.98
Pritt and Chern, 2018	Deep learning	fMoW	–	0.79
Azzouzi et al., 2018	Gaussian Radial Basis Function	USGS Landsat 5	Algeria	0.93
(Zhang et al., 2020b)	Convolutional Neural Network	SAR	Ottawa	0.90
Liu et al., 2018a, 2018b, 2018c, 2018d	Deep Convolutional Neural Network	SAR and optical	UK	0.97
Saha et al., 2019a	Deep change vector analysis (DCVA)	VHR WorldView 2	Italy	0.98
Jin et al., 2019	Deep Convolutional Neural Network	NGS	China	0.96
Zhang and Shi, 2020	Convolutional Neural Network	VHR World View 3	–	0.92
Ren et al., 2020	Generative Adversal Network	VHR	–	–
Saha et al., 2019b	Deep Change Vector Analysis	VHR World View 2, Pleiades, and Quickbird		0.96
Touati et al., 2020	Deep Sparse Residual	VHR WorldView2, Quick Bird2	–	0.96
Kalinicheva et al., 2020	Unsupervised approach	HR	–	–
Zhang and Shi, 2020	Convolutional Neural Network	AID	China	0.50

sensing with its issues and challenges.

Further study is categorized into different sections. In section II, the change detection procedure is discussed and Section III describes the different approaches being used for the detection of changes. Section IV presents the metrics of performance evaluation. At last, Section V gives a brief discussion and conclusion of the study.

2. Change detection procedure

Remote sensing data is commonly used to detect the scale of change that include a significant change in two different images with respect to a distinct period. The differences are identified to constitute a change map. Fig. 1 explains the complete process of detecting the changes within two images. The process of change detection method starts with data collection, where a series of images are taken from the same location at different periods (Landsat Acquisition Tool, 2021). It has been realized that it is imperative to apply the process of preprocessing on targeted images to check the atmospheric effect and noise. After completing the task of preprocessing, the change detection algorithms need to apply to detect the scale of variability.

Table 5
Comprehensive Analysis of advanced models for the detection of changes.

Authors	CD Approaches	Images	Area	Accuracy
(Xu et al., 2017)	Empirical orthogonal function (EOF)	Landsat	Jiangsu, china	89.25
Wang et al., 2014	Resolution land cover change detection (RLCCD)	Landsat 7	Liaoning, china	–
(Marinelli et al., 2017)	Spectral change vectors (SCVs)	Multitemporal HS images	Washington, USA	–
Yan et al., 2018	Hybrid Spectral Difference (HSD)	WorldView 2 VHR Landsat 7 EMTM	China	–
Ma et al., 2019a, 2019b	Image Mapping	Homogeneous dataset (SAR) Ottawa dataset	Chine	0.97

2.1. Image preprocessing

To address the problem of atmospheric effects such as unwanted noise or objects, researchers have developed different image processing methods. It is hard to distinguish among various ground artifacts with human vision due to the spatial resolution of satellite images. False-color variation helps to classify the ground artifacts and helps to detect the efficacy of the change map (Ma et al., 2017). Fig. 2 shows the different methods of satellite image preprocessing for change detection.

2.2. Geometric registration

Geometric registration is a solution that helps to detect unavoidable parts of satellite images to analyze change (Wu et al., 2014; Zhang et al., 2016a, 2016b). This approach is primarily employed to detect the changes in images that are captured in multiple dimensions that can be a reason for the misclassification of the pixels. To operate geometric registration, Rational Polynomial Coefficient (RPC), Digital Terrain Model (DTM), Scale-Invariant Feature Transform (SIFT), Particle Swarm Optimization Sample Consensus (PSOSAC), Continuous Ant Colony Optimization (CACO), and Random Sample Consensus (RANSAC) are proposed (Fytsilis et al., 2016; Wu et al., 2017; Wu et al., 2019). Apart from these methods, one more registration approach named as Harris-Laplace is employed for change detection (Cao et al., 2016). In this method, the identified points are clustered and balanced using SIFT to improve the accuracy of point detection.

2.3. Radiometric correction

To normalize the multi-temporary data obtained over different periods, relative radiometric correction can be applied. While comparing several data sets, it has been analyzed that the process of image enhancement and correction is performing a significant role (Franklin and Giles, 1995). Here, the radiometric correction method enhances the interpretability and consistency of remotely sensed data. Radiometric correction is a series of methods designed to transform the digital values of the sensors such as radiance, specular reflection, and surface temperature (Pons and Arcalís, 2013). For stabilizing the brightness and contrast in the satellite images, the intensity normalization method is performed. It can be evaluated by changing a satellite image histogram as per requirement (Wan et al., 2018). Radiometric corrections are also utilized in the Digital Elevation Model (DEM) to improve the incident-angel oriented surface area (Ajadi et al., 2016). Sensors that causes adjustments in scene illumination and geometric corrections are removed by radiometric corrections that eliminate geometric distortions.

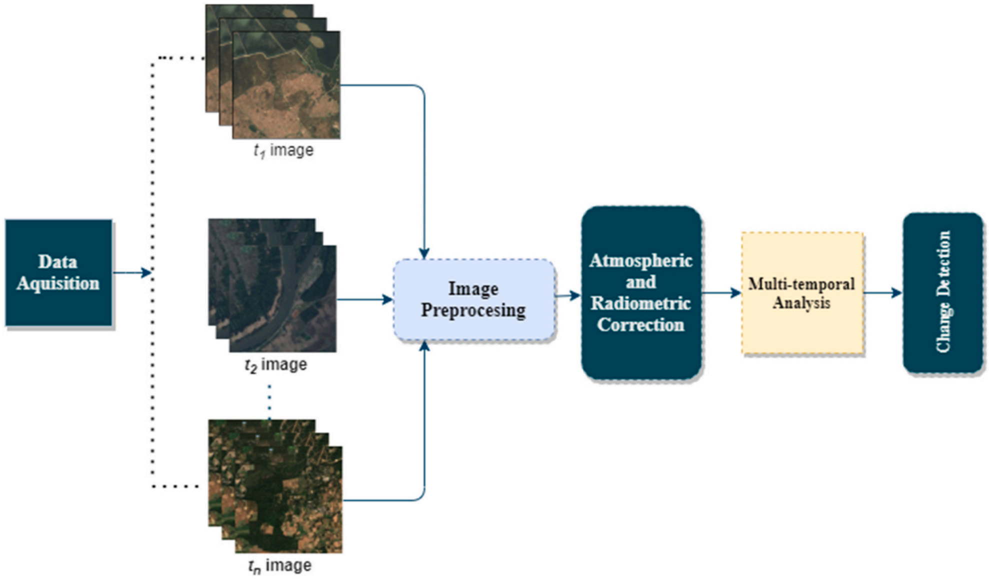

Fig. 1. Flow to detect the changes from satellite imagery.

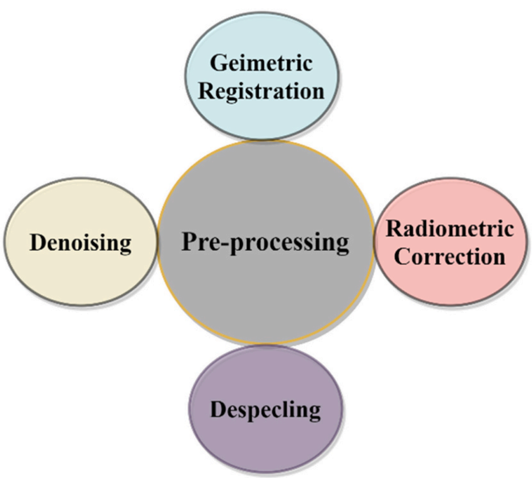

Fig. 2. Some basic satellite image preprocessing techniques for change detection

2.4. Despeckling

Despeckling is mostly used to minimize noise as well as retain the information of the image. The pixel intensities are typically influenced by additive gaussian noise in optical images. Rather than utilizing Landsat 8 images, Synthetic Aperture Radar (SAR) images are commonly used in change detection. SAR images contain less amount of atmospheric effects or clouds. However, the speckle noise may influence the image's pixels in the SAR image. Researchers have developed different methods to increase the efficacy of the techniques to detect changes in SAR images (Zhang et al., 2020a). To eliminate multiplicative noise in SAR images, spatiotemporal speckle filtering is used (Wang et al., 2017). Another filter such as Lee sigma filter used on SAR images for despeckling (Iino et al., 2018). In the process of despeckling, Lee sigma filter showed a better result, among other filters. On the other hand, the Gaussian noise model was developed that was widely used to eliminate Gaussian noise (Golilarz et al., 2019; Masse et al., 2018). The pixel values are determined by analyzing the complete image instead of considering the neighborhood pixels of an image. In (Feng and Chen, 2017), nonlinear diffusion filtering is proposed to deal with the speckle noise in SAR images. Moreover, to denoise SAR images, a non-local mean filter is presented (Devapal et al., 2017). In (Reich et al., 2018), a real-time image dimensionality reduction filter is proposed that uses a thresholding-based approach to identify the edges of the images. Adaptive Cuckoo Search is another method based on optimal bilateral filtering to accelerate the convergence of the bilateral filter control parameter (Asokan and Anitha, 2020).

3. Approaches-based on change detection

To analyze the scale of urban growth, the primary objective of change detection methods has to analyze the condition of a specific location to identify variations from the images captured at different periods. Through satellite-based remote sensing, high spatial and spectral resolution-oriented images are captured that are used to analyze the scale of change. Based on its implementation, different methods for the identification of changes have been introduced in Fig. 3.

3.1. Algebra-based change detection techniques

To identify the scale of change, algebraic expressions are utilized to evaluate each pixel of an image in algebra-based change detection techniques. Image differencing (Ke et al., 2018), Image rationing (Liu et al., 2015), Change Vector Analysis (CVA) (Ferraris et al., 2017), and Image regression (Ridd and Liu, 1998) is the most common algebra detection methods. The selection of a threshold value is considered the most imperative process in standard algebraic change detection techniques that helps to detect the targeted region of an image to analyze the scale of change. These solutions are easy to implement, however, it is difficult to select an acceptable value of the threshold that can cause poor determination of the scale of change. The major drawback of these approaches is the classification of the areas from the images that contain a high ratio of noise. An unsupervised change detection approach is introduced to determine change vectors and statistical parameters by utilizing the Expectation-Maximization (EM) algorithm (He et al., 2014). The change vectors help to identify the image variance and the EM algorithm is used to compute its statistical parameters. In (Qi et al., 2015a, 2015b), three mechanisms such as object-oriented image analysis, Post Classification comparison (PCC), and PCA are utilized to analyze the change that significantly minimized the rate of false alarms.

Image differentiation is a procedure that is used to analyze the grey-scaled images to access spatial information from the images. In the process of image processing, a variation in two images can be analyzed

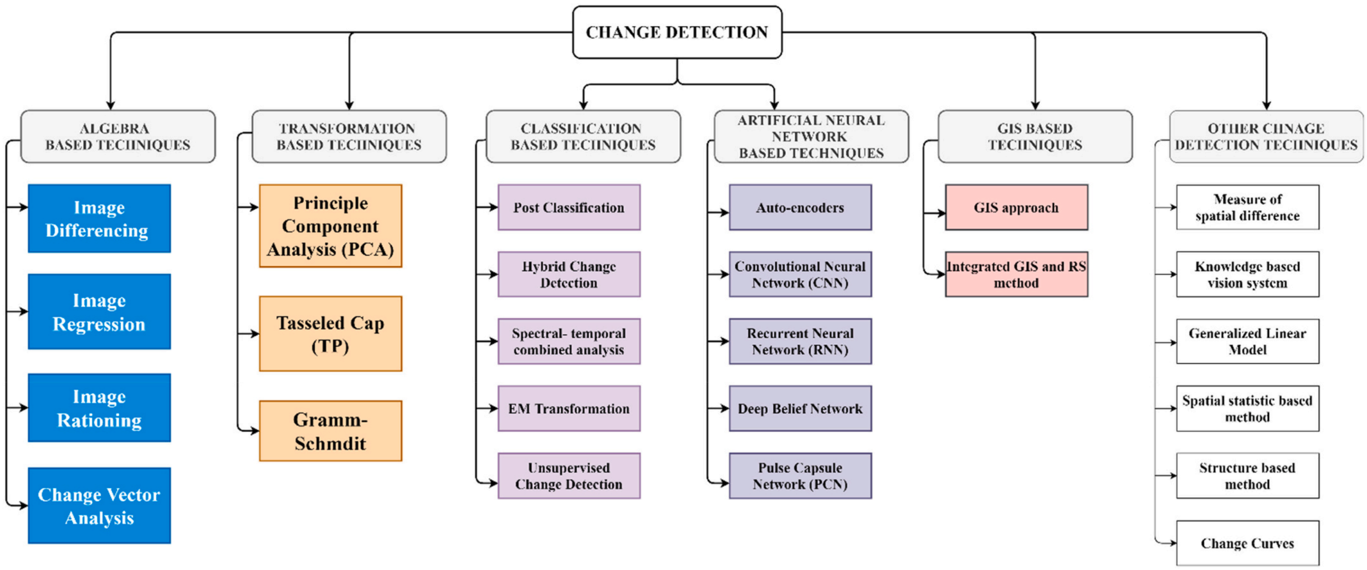

Fig. 3. Different approaches for detection of change

adequately by accessing the intensity of pixels in grey color (Minu and Shetty, 2015). Change vector analysis is another change detection technique that describes the evolutionary nature of multispectral images. In this manner, it has been analyzed that the algebraic change identification methods are easy to implement and simpler to apply on images to detect the scale of change.

3.2. *Transformation based change detection technique*

The change detection also includes the use of pixel transformation to detect the scale of change in the images by utilizing transformation techniques such as Principal Component Analysis (PCA) (Abdi and Williams, 2010), Tasseled Cap Transformation, and Chi-Square Transformation (CST) that are illustrated in Figs. 4 and 5 for better understanding. While implementing a transform-based change identification process, the redundant bands are reduced by decomposing the objects and the change is observed through transformation. In the case of fast detection of changes for reference images, the Homogenous Pixel Transformation (HPT) technique is proposed (Liu et al., 2018a, 2018b, 2018c, 2018d; Liu et al., 2016). The main disadvantage of this approach is, it is difficult for labeling the changing area in the image. (See Fig. 6.)

3.3. *Classification-based change detection technique*

The classification approach is completely dependent on the selection of data for change analysis. As the change detection accuracy is not affected by external factors such as atmospheric disturbance, this is considered as one of the most influential advantages of this approach. By utilizing the classification-based change detection technique, the better outcomes related to the change recognition can be achieved, however, the proposed solutions are suffering from the limitation of the training data. The scale of change is determined by following the concept of multi-dimensional distribution and the variables are determined by implementing the Expectation-Maximization (EM) algorithm (Prendes et al., 2015). To determine the area of land, an unsupervised classification approach is proposed named as for Ensemble Minimizing Learning Algorithm (EML) that categorize the multiple images into clusters (Vignesh et al., 2016). However, as the size of the samples is limited, the value of the predictive outcome is unsatisfactory. For multi-temporal satellite images, Principle Component Analysis (PCA) is combined with an available classification if urban levels change in the river delta, can be efficiently monitored (Li and Yeh, 1998; Li et al., 2010).

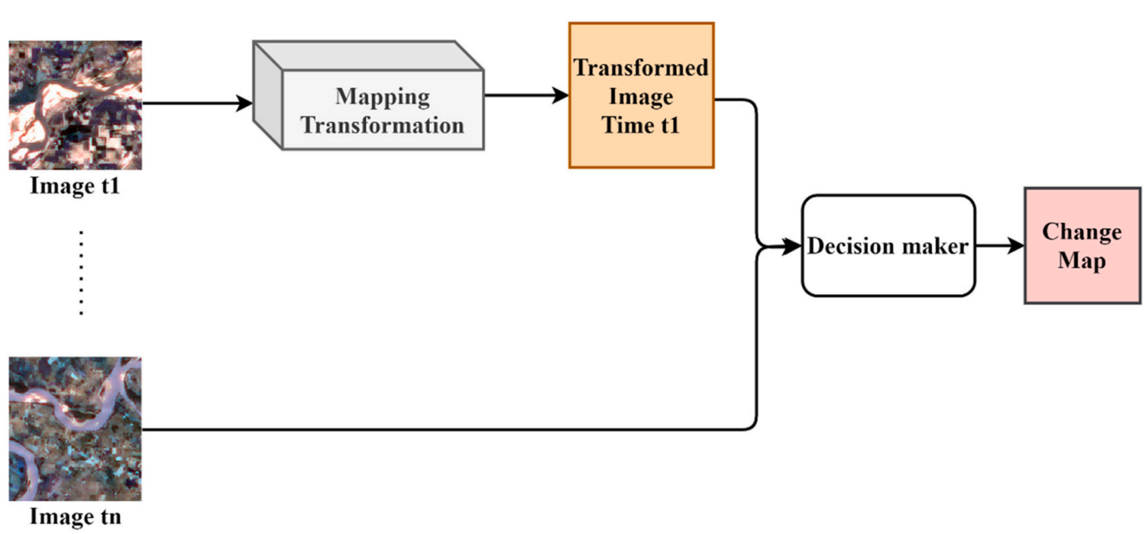

Fig. 4. Transformation based change.

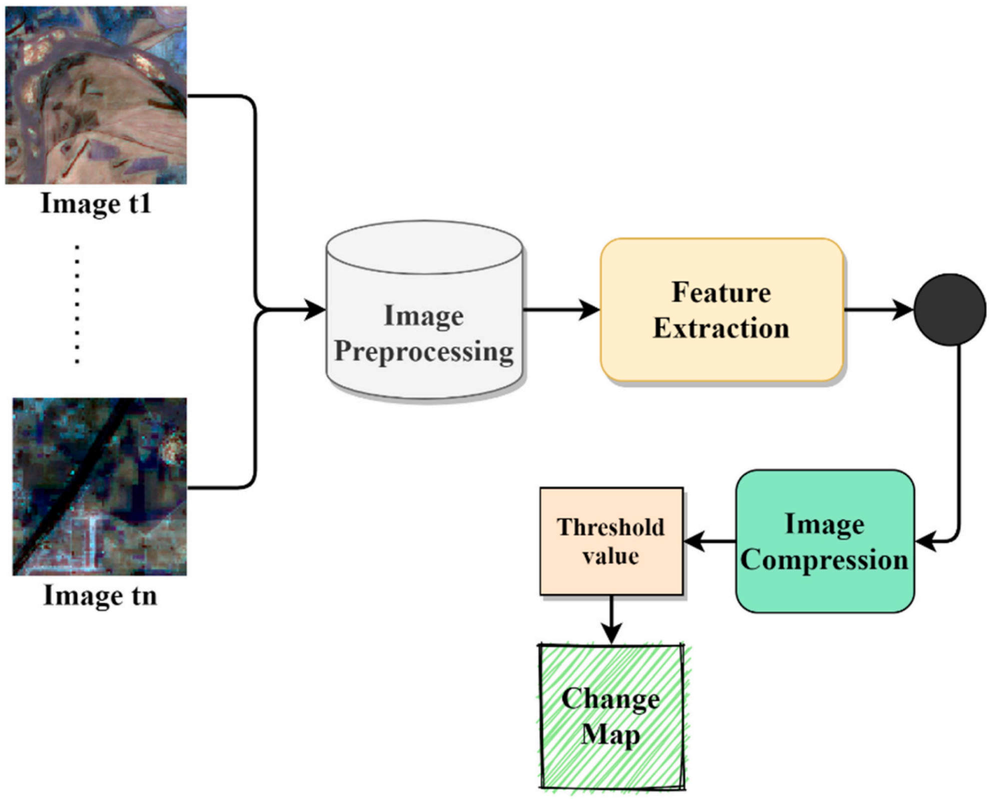

Fig. 5. Principal Component Analysis (PCA) detection framework

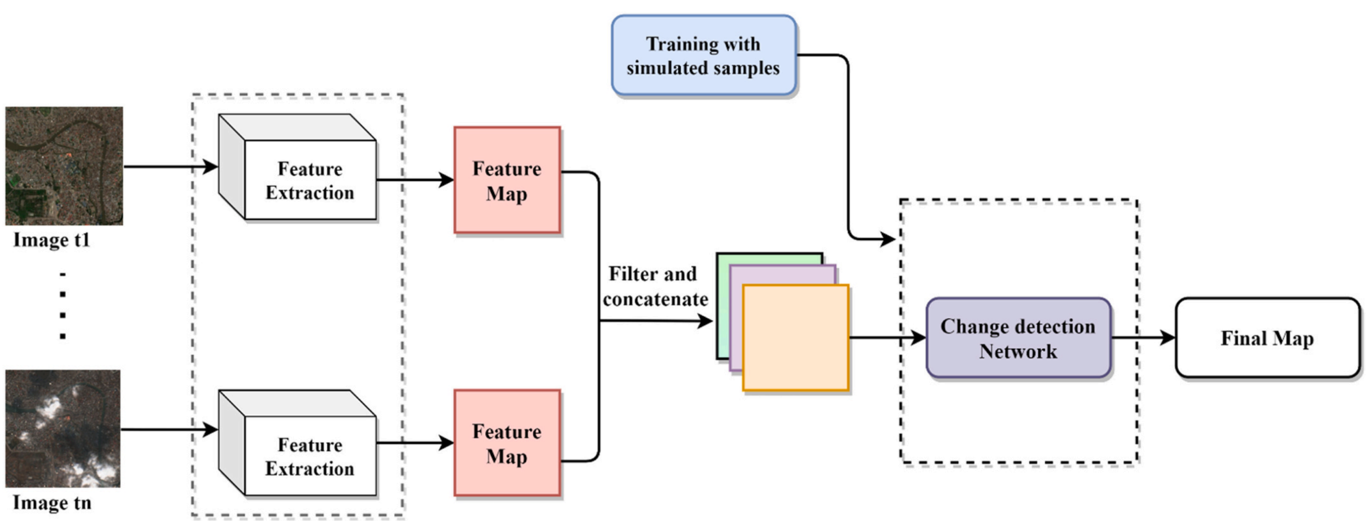

Fig. 6. Classification based change detection (Ji et al., *2019*).

3.4. Advanced models for change detection

The advanced method of identification of changes consists of various reflection and spectral mixing models. In these approaches, the image value is transformed into a substantial variable by following the concept of linear pattern analysis. (Wang et al., 2014) has introduced a Hopfield Neural Network (HNN) model (Li et al., 2014) to analyze the condition of the land. Another change detection method named a temporal unmixing method is proposed by (Xu et al., 2017) that analyzes the landscape images to identify the change in the coverage area. A hybrid spectral change-based change detection approach is explored by (Yan et al., 2018). This approach defines the differences between the spectral values and shapes, and it requires only spectral features to defines the modifications which are not readily detectable. This method is also suffering from the problem of over-clustering that defines the limitation in the prediction of change with respect to the predefined classes. In this manner, developing a model for the conversion of reflectance value is considered as a big challenge in advanced models.

3.5. Artificial neural network and fuzzy-based change detection techniques

Several new methods have incorporated in Artificial Intelligence (AI) techniques that enhanced the scale of precision for change detection. A wide variety of Remote Sensing (RS) research has suggested the superiority of AI-based change detection approaches over the conventional approach for extracting the features from the images (Zhang and Lu, 2019; Fang et al., 2019). The neural network-based approach consists of assessing the area of change by using a combination of different neural network approaches, blurred method, and remote sensing techniques.

By following the proficiency of AI techniques for feature extraction and learning, the evaluation of real-world geographical features has become possible with significant accuracy. Fig. 7 illustrates different AI-assisted frameworks that are specifically designed to analyze the change from the extracted feature maps. Based on the process of in-depth feature extraction and training, the AI-based change detection frameworks can be categorized into three types: Single-stream framework, Double-stream framework, and Multi-modal integrated structure.

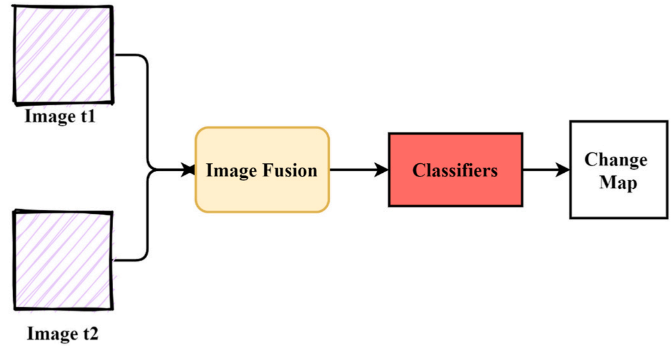

Fig. 8. Direct Classification structure

3.5.1. Single stream framework

In single-stream frameworks, only one primary AI method has to embed in the predictive solution to identify the change. The categorization of the single-stream frameworks can be done in two categories such as direct classification structure and transformation-based mapping structure as represented in Fig. 8. It is imperative to mention that several studies have updated the solutions for fulfilling the objective of change detection with respect to the need for application and domain (Shi et al., 2020a, 2020b).

3.5.2. Double stream framework

The double-stream structures are always been preferred to recognize the change by analyzing the images which are captured at two different time-stamps. Moreover, these methods can broadly categorize into three categories such as Siamese structure (Arabi et al., 2018; Jiang et al., 2020; Varghese et al., 2018; Zhan et al., 2017), transformation-based structure, and post-classification form (Bruzzone and Cossu, 2002; Abuelgasim et al., 1999; Lyu et al., 2018; Cao et al., 2019) as illustrated in Fig. 9 and Fig. 10.

3.5.3. Multi-model integrated structure

The multi-model integrated framework is a hybrid structure similar to a double-stream design. Change detection is the spatiotemporal analysis that can be achieved by acquiring the spatial and temporal features from the sequence of frames. In multi-model structures, both spatial and temporal features are utilized to analyze the scale of change. The spatial features are utilized to analyze the change patterns and temporal features are utilized to analyze the dependency of change over spatial features captured on different time-stamps (Chen et al., 2020; Song et al., 2018; Mou and Zhu, 2018; Liu et al., 2019a, 2019b). Several different architectures such as Auto-Encoders (AEs), Deep Belief Networks (DBNs), Convolutional Neural Network (CNN), Recurrent Neural Networks (RNNs), and Pulse Capsule Neural Network (PCNNs) are also used for change detection (Gong et al., 2017a, 2017b; Han et al., 2019).

3.5.3.1. Auto-encoder (AE). Auto-encoder can be used to reduce the dimensionality of a component. It is widely used in for feature extractor, as, it has the robust feature learning capability of neural network. The commonly used AE models are stacked auto-encoders (De et al., *2017*, Planinšič and Gleich, 2018), stacked denoising auto-encoders (Zhang et al., 2016a, 2016b, Su et al., 2016, Su et al., 2017), stacked fisher auto-encoders (Liu et al., 2019a, 2019b), Sparse auto-encoders (Fan et al., 2019), and denoising auto-encoders (Li et al., 2018). These auto-

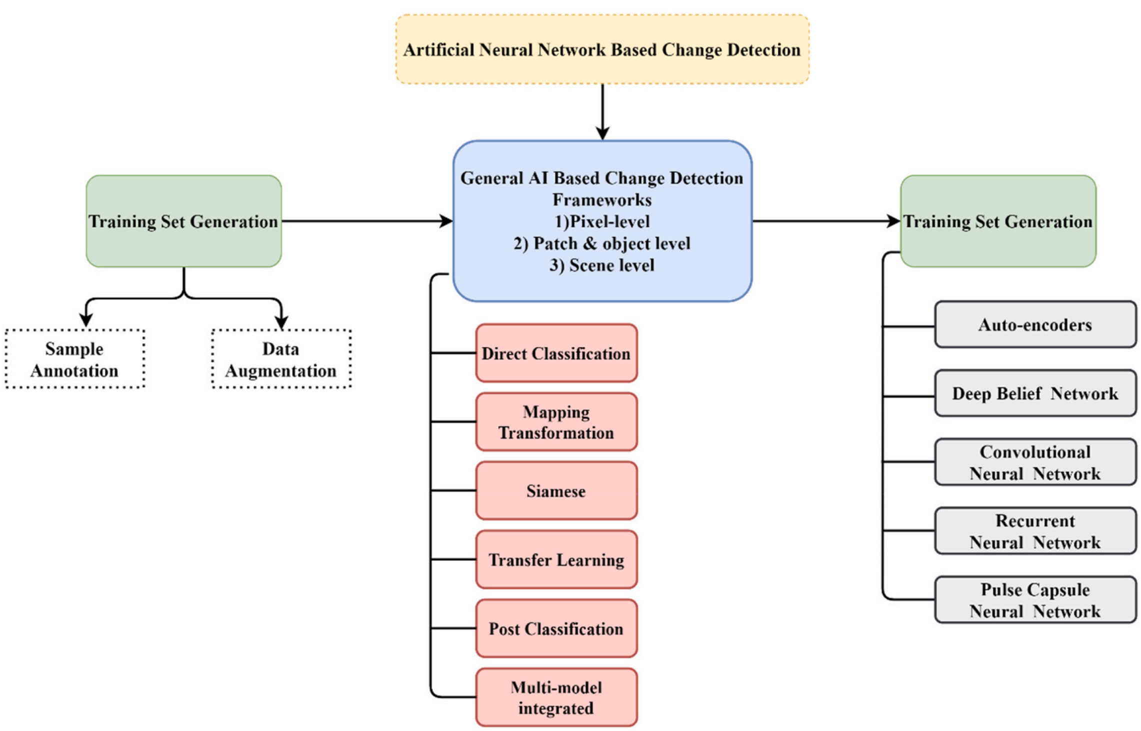

Fig. 7. AI-Based Change detection techniques.

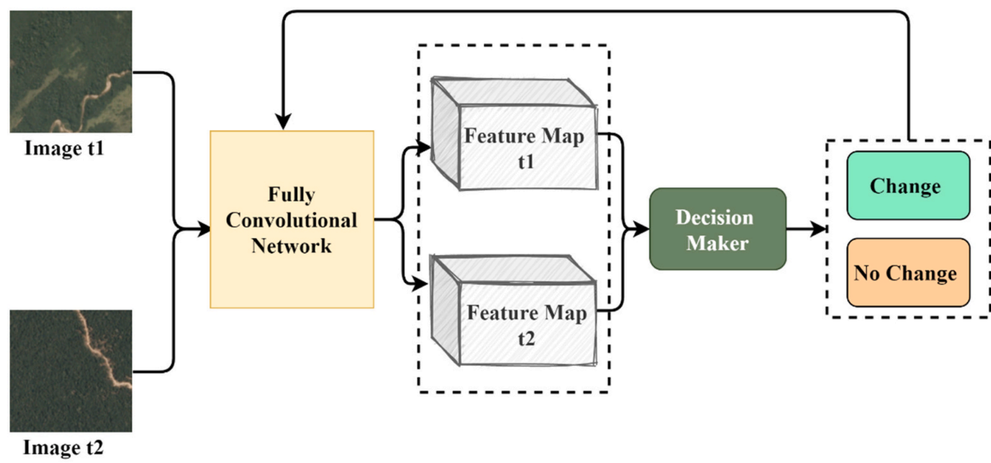

Fig. 9. Siamese framework for change detection.

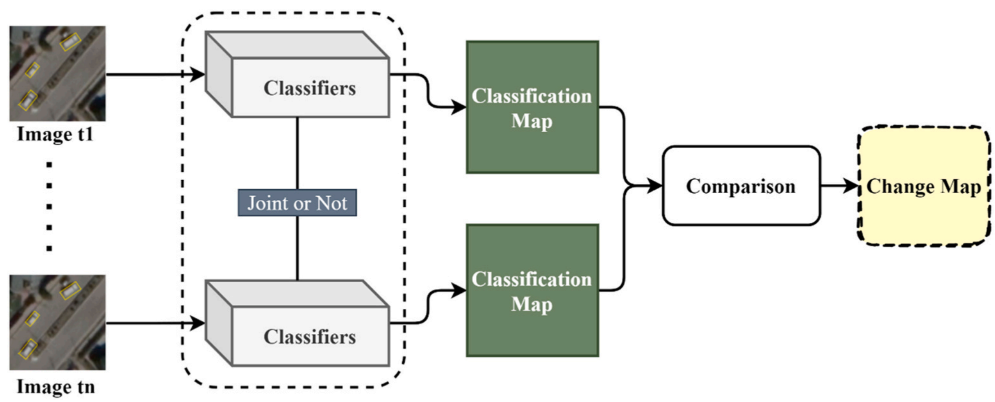

Fig. 10. Post classification structure

encoders maintain spatial information by extending pixel neighborhood values into vectors. In contrast, convolutional auto-encoders are implemented directly by convolution kernels (Kerner et al., 2019). Depending on its features, auto-encoders can detect changes in an unsupervised manner and work effectively.

3.5.3.2. Deep belief network (DBN). A deep belief network is a generative statistical approach that learns to rebuild its inputs empirically. The deep belief network consists of several hidden layers that are responsible to make interactions between the layers. However, the units within the same layer are not connected and each hidden layer serves as a transparent layer for the next layer. It can be greedily trained, i.e., one layer at a time, and appears in many unsupervised image processing techniques (Cao et al., 2017; Chu et al., 2016; Samadi et al., 2019). A DBN-assisted framework is proposed for the classification of numerous changes from an image (Su et al., 2017). The proposed solution incorporated a greedy layer-wise training approach that dramatically eliminates the problem of overfitting.

3.5.3.3. Convolutional neural network (CNN). CNN techniques are effectively utilized in a wide range of remote sensing applications such as land use Land cover, object detection, feature extraction, and change detection (Gong et al., 2015; Liu et al., 2016; Lyu et al., 2018; Puig et al., 2002). It is used to improve the other change detection techniques and to learn the non-linear mapping between modified and unchanged image pairs (Gong et al., 2017a). Due to the strong capability of feature learning from images, CNN becomes the best choice for researchers when training samples are sufficient (Chatfield et al., 2015; Peng and

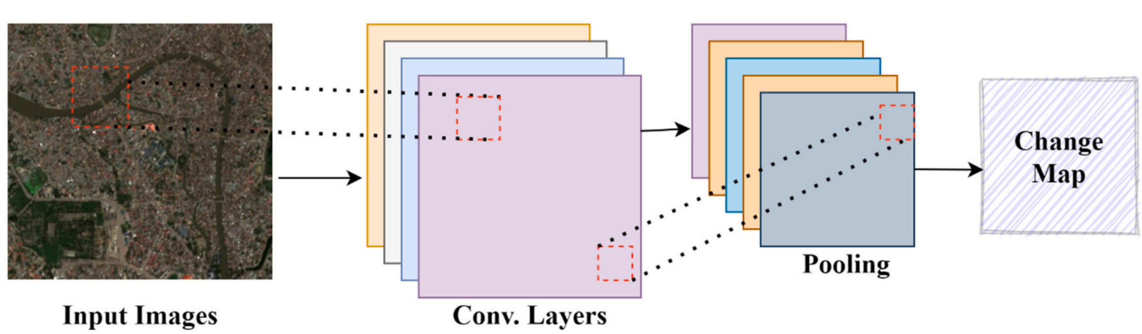

Fig. 11. Convolutional neural network.

Guan, 2019). The procedure of extracting information from images is illustrated in Fig. 11.

CNN architecture incorporates the convolutional layers with sub-sampling operations that decrease design complexity and improves the capability of generalization with less trainable parameters (Krizhevsky et al., 2017; Gong et al., 2015; Liu et al., 2016; Lyu et al., 2018). By considering the ability to learn the extracted features from an image, CNN has obtained a considerable performance in various image analysis tasks. Many classical CNNs and their extensions such as VGGNet (Peng et al., 2019, Nemoto et al., 2017; Sakurada and Okatani, 2015), CaffeNet (El Amin et al., 2016), SegNet (Zhu et al., 2018), UNet (Peng et al., 2019), InceptionNet (Pomente et al., 2018), and ResNet (Venugopal, 2020a, 2020b) are used as a classifier. A multiscale convolutional neural network (CNN) model is proposed by (Zhang et al., 2020a) that trained the model on non-normalized images for securing the more details of an image. Moreover, to learn deep features for the detection of change, spatially registered images are required for CNN (Guo et al., 2018). To detect the complex features from high-resolution satellite imagery, a Deep Difference Convolutional Neural Network (DDCNN) is proposed by (Zhang and Shi, 2020). While training the CNN model, a huge amount of labelled data is required for the detection of change that is addressed in SemiCDNet model which is developed by (Peng et al., 2020). Hence, the use of CNN has changed the process of image analysis, there is still no systematic way to design and train the network which would be considered a long-standing issue in the remote sensing community.

3.5.3.4. Recurrent neural network (RNN). As the task of change detection involves data with respect to multiple periods, the input can be converted in the form of a process that obtains the information related to change from the data sets (Shi et al., 2020a, 2020b). RNN techniques have received considerable attention to solving many complex issues involving sequential time series data, in particular Long Short-Term Memory (LSTM) models (Ordóñez and Roggen, 2016). To detect the changes from satellite images, it is necessary to provide a stable framework for the expression of data extraction for change detection. In this manner, RNN represents the feasible methods for learning imperative information for the detection of change from sequential time-series remote sensing data (Lyu et al., 2016; Chen et al., 2020). However, due to vanishing gradient problem in RNN, the enhanced version of RNN named as Long Short-Term Memory (LSTM) network alleviates gradient disappearance and gradient explosion from the sequential data (Lyu et al., 2016; Song et al., 2018, Liu et al., 2019a, 2019b). The researchers have utilized LSTM networks to obtain changes from the multi-temporal RS data (Lyu et al., 2016). The trained model could be transferred to other data domains with an adequate generalization capacity. Fig. 12 shows the core directive part in the form of a directed graph that can be unfolded to a chain of series-connected units (i.e., RNN cells).

3.5.3.5. Pulse capsule neural network. The pulse capsule neural network (PCNN) is a bionic neural network focused on the primate's visual cortex (Of, A. R., Coupled, P., and Network, N, 2019). Unlike conventional neural networks, the learning and training phase does not require the extraction of successful information from very complex backgrounds in PCNN. The pulse neural network (PCNN) takes two-dimensional image data and each neuron correlates to a single pixel of an image. The pixel value acts as an external stimulation for each neuron that interconnects the adjacent neurons and supply regional stimuli to the next connected neurons. External and regional stimuli are mixed in a modulation field with a pulse generator to generate the output. As the duration of training increases, the PCNN produces a pulse sequence that can be used for the segmentation and extraction of the features from the images (Dewan et al., 2019) and, similarly, for the detection of change (Benedetti et al., 2018, Huang et al., 2019, Ma et al., 2019a, 2019b).

3.5.4. *Fuzzy clustering technique*

The detection of change from a Synthetic Aperture Radar (SAR) by utilizing a fuzzy clustering approach from an image is introduced in (Li et al., 2016). The primary benefit of these approaches is, it has the ability to handle the noise in an effective manner. Different studies investigate the detection of changes by utilizing deep learning approaches (Huang et al., 2018; Huang et al., 2019; Huang et al., 2018). To enhance the ability of change detection, a combination of fuzzy and Markov random fields is proposed (Subudhi et al., 2014). Table 6 provides an in-depth analysis of the all the above-dicussed ANN and fuzzy-based approaches with their respective areas.

3.5.5. *GIS-Based change detection*

A Geographical Information System (GIS) incorporates various sources of information in the detection of change. The main benefit of using GIS is to identify a change in the area that is being examined in a regular manner. It has been analyzed that multiple sources of data affect the performance of the model. However, the GIS method is more effective for handling and visualizing the multidimensional data in the field of remote sensing. GIS incorporates quantitative data sources and makes it much easier to obtain and analyze information on the detection of changes. Detection of vegetation cover changes using remote sensing and utilized the Normalized Difference Vegetation Index (NDVI) to categorize the vegetations (Gandhi et al., 2015). GIS-inspired Land cover change detection with remote sensing is introduced by (Rawat and Kumar, 2015). The proposed solution makes it easier to detect improvements with better accuracy and lower cost.

3.5.6. *Other change detection techniques*

Besides the popular categories of change detection, some other approaches are also used to detect changes in multi-temporal remote sensing images (Mohamed and Mobarak, 2016; Pasanen and Holmström, 2015; Lv et al., 2016). In (Feng et al., 2018), objects are identified accurately and neighborhood similarity is measured by utilizing an object-based change detection approach. The biggest challenge of this approach is to deal with scattered and distributed samples. In

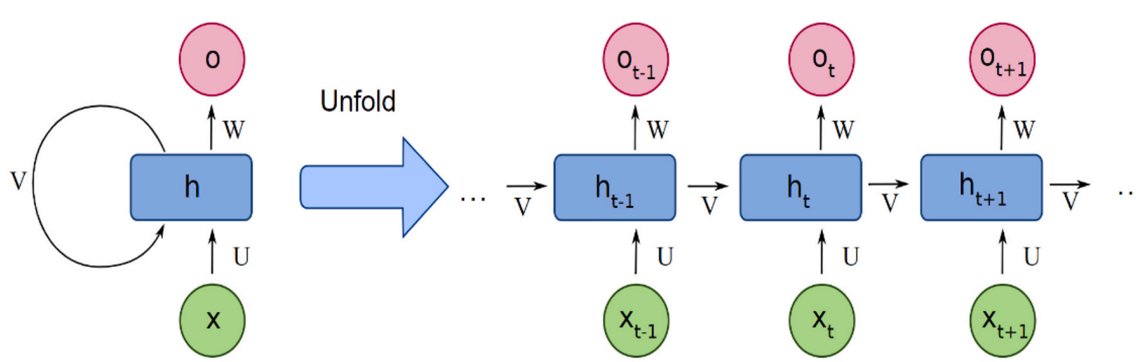

Fig. 12. Recurrent neural network (RNN).

Table 6
Detailed survey on neural network and fuzzy-based change detection.

Authors	CD Approaches	Images	Area	Accuracy
Subudhi et al., 2014	Gibbs Markov Random Field (GMRF)	Landsat	Italy	–
Li et al., 2016	Multi-objective Fuzzy Clustering	Ottawa dataset	Bern, Switzerland	0.95
Su et al., 2016	Deep learning and Mapping (DLM)	Chanba Dataset Farmland dataset SAR	Chamba Shuguang Estuary	0.96
(Tian and Gong, 2018)	Edge-weighted fuzzy clustering	SAR Ottawa dataset	Bern	0.78
Huang et al., 2018	Semi-transfer deep convolutional network (STDCNN)	WorldView 3 Worldview 2	Hong Kong Shenzhen	0.91
Huang et al., 2018	Object-oriented change detection	IKONOS images	Tang Jiao	0.92
Jing et al., 2020	SLIC-CNN and CAE Features	Google Earth	Beijing, Wuhan	0.95
Zhang et al., 2020b	Essemble CNN	WorldView-3. UAV	–	0.92
Kalinicheva et al., 2020	Deep learning with Graph-based approach	Sentinel-2 and SPOT-5	–	–
(Karim and van Zyl, 2020)	Deep Learning and Transfer Learning	Sentinel-1 and Sentinel-2	–	0.85
Wang et al., 2020	Deep Siamese Network	ZY-3 and GF-2	Dalong Lake and China	0.97
Song and Choi, 2020	Fully Convolutional Network and Transfer learning	KOMSAT-3A	Korea	0.97
Zhang and Shi, 2020	Convolutional Neural Network	WorldView-3, Quickbird, and Ziyuan-3	–	–
(Seydi et al., 2020)	Convolutional Neural Network	PolSAR	Abudhabi, (UAE)	0.98
Shi et al., 2020a, 2020b	Deep Neural Network	OSM	Hong Kong	

(Yang et al., 2017), the authors described a vegetation cover change study by following Multivariate Adaptive Regression Splines (MARS) model and the Back-Propagation Neural Networks (BPNNs) model-assisted a hybrid approach. Another change detection approach for remote sensing data is proposed in (He et al., 2015), which utilized an advanced Markov model to deal with the local ambiguity. Therefore, the need for high computation resources is considered as one of the major disadvantages (Gu et al., 2017). (Han and Zhou, 2017) introduced the Adaptive Unimodal Subclass Decomposition (AUSD) learning system to analyze change with respect to the land. For estimating change from heterogeneous images, a fusion-based FastMap approach is followed is proposed by (Touati and Mignotte, 2017).

4. Accuracy assessment

The evaluation of the performance is necessary to evaluate the findings and to determine the issues. Due to the presence of a temporal feature in the remote sensing data, the assessment of accuracy is difficult to calculate. Moreover, the prediction accuracy is also dependent on several aspects such as image quality (White and Engelen, 1997); pre-processing (Roy, 2000); the correlation between the spectral channels and images, and sampling strategies (Li et al., 2018). However, (Congalton and Green, 2019) argued that the correlation between layers contributed to the accuracy, where the sum of the product would be applicable to separate classified layers. There are several common methods present that are used to evaluate the prediction accuracy of an image.

To evaluate the outcomes related to the detection of change, accuracy evaluation based on the error matrix is commonly used. The detection of changes is expressed in a binary map where the modified regions are displayed in white pixels and the unchanged regions in dark pixels. The widely used performance measures are Overall accuracy, False alarm rate, Missed Alarm Rate, and Total Error Rate (Sadeghi et al., 2018; Bruzzone and Prieto, 2000; Zhuang et al., 2017a; Liu and Zhou, 2004). Different methods such as the matrix of change detection error (Macleod and Congalton, 1998), area-based accuracy(Lowell, 2001), the curve of accuracy assessment (Morisette and Khorram, 2000), and rule-based rationality (Liu and Zhou, 2004) are suggested in different studies that are utilized to evaluate the accuracy with respect to the detection of changes. While interacting with multiple images for change analysis, the calculation of the error definition matrix is always challenged. To deal with this issue, (Li and Zhou, 2009) suggested a trajectory error matrix that detects numerous changes. The kappa coefficient (Zhuang et al., 2018) is just another valuable indicator that evaluates the detection of algorithms proficiency calculated as:

$$\mathbf{kappa} = \frac{(\mathbf{k1} - \mathbf{k2})}{(\mathbf{1} - \mathbf{k2})} \tag{1}$$

Here k1 and k2 are evaluated by Eqs. (2) and (3).

$$\mathbf{k1} = \frac{\mathbf{Chnaged\ Pixels\ (CP) + Unchanged\ Pixels\ (UP)}}{\mathbf{Total\ number\ of\ Pixels\ (TP)}} \tag{2}$$

$$\mathbf{k2} = \frac{\mathbf{(CP + MA)(CP + FA) + (FA + UP)(MP + UP)}}{\mathbf{TP^2}} \tag{3}$$

Changed pixels (CP) indicate the pixels that are detected and marked as changed. The Unchanged Pixels (UP) represent the pixels that are marked as unchanged. Similarly, TP is the total number of pixels. The majority of the unaffected pixels found as modified pixels are considered as the False Alarm (FA). CP, UP, MA, and FA are the sum of TA**.** The change detection algorithms are directly proportional to their accuracy and recall values.

5. Discussion and conclusion

A change detection approach becomes considerably acceptable if it provides details about change areas, accurately identifying the change forms, and better understanding the detection of change outcomes. The scale of accuracy is completely dependent upon the quality of the dataset, data complexity, domain of study, and the method opted to perform the task of change detection. This study discusses an overview of different techniques and stages that are essential for the detection of changes. The limitations of each method for the detection of change are highlighted and presented in Table 7.

The data related to remote sensing is always dependent upon the need of the application. The accessibility of satellite information additionally plays a vital role in the detection of change. After reviewing the different research works, it has been concluded that the post-classification-based approach delivers considerable accuracy as compared to the algebraic approaches. There are numerous techniques for detecting changes; however, it is difficult for selecting an optimum and definite method. As detection of change is considered as one of the challenging areas, data analysts are implementing different techniques by applying their skills to detect change. However, processing the heterogeneous data is considered as one of the most common challenges in change detection.

Due to advancements in technology, satellite image processing is considered as an appropriate technology for remote sensing applications. In the traditional image processing methods, the collection of the satellite images, computational approach, and the impact of disturbance

Table 7
Change detection approaches with their benefits and limitations.

Sr. No	Approaches	Advantages	Challenges/Limitations
Algebra based change detection techniques			
1	Image Differencing	Execution is simple and basic	This approach does not give a point by point matrix, and also it requires an acceptable range
2	Image Regression	Diminish the effect of atmospherical and environmental variations between reference images	Requires precision regression function for developing this approach
3	Change vector analysis	Capacity to handle more bands of spectrum	Complexity in recognizing the land cover change (LC)
Transformation based change detection technique			
1	Principal Component Analysis (PCA)	The repetition of information diminishes	It can't give a total matrix to change data and require an edge to recognize the progressions that happened in the territory.
2	Tasseled Cap (TC)	Reduce the amount of data between bands	It is inconvenient to interpret and probably won't offer an entire matrix of changes.
Classification based change detection approach			
1	Post Classification Comparison	Reduce the impact of atmospheric	This classification requires more time to produce. The image quality relies upon a definitive precision.
2	Unsupervised Change Detection	An unsupervised technique utilizes a clustering approach.	The change path is hard to recognize and label.
Advanced models for change detection			
1	Spectral Mixture Model	The outcome is steady and precise	Implementation compared to other methods is complicated.
Visual based changed detection approach			
1	Visual Interpretation	During analysis, human expertise and information are useful.	Incapable of giving a point by point data that has been changing but consumes more and more time to update the result.
Gis based change detection approach			
1	GIS approach	It allows mapping the changes in the image of the present and past data	Performance of results varying in mathematical and classification process.
2	Integrated GIS and RS method.	It empowers the elucidation and investigation of information to be accessed	Detailed data from various sources change the identification.

on the satellite images were considered as the most common issues. Advanced data analysis methods are developed for overcoming the limitations of the traditional image processing approaches. In the past few years, deep learning techniques have increased the efficiency of data processing provided considerable prediction outcomes. In this manner, it has been concluded that the development of deep learning-assisted hybrid approaches can help to obtain promising outcomes with respect to the domain of change detection.

Declaration of Competing Interest

None.

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