A STUDY ON LAND USE AND LAND COVER CHANGE DETECTION USING NEURAL NETWORK TECHNIQUES

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Abstract: Land Cover Change Detection (LCCD) for GIS (Geographic information system) is a technique that accesses the importance of a particular region that has been changed between two or more time periods. Remote sensed data have become a primary source in observing land cover changes at different scales. Digital Change Detection is a process that aids in detecting the changes related to land use and land cover area with reference to high resolution multitemporal remote sensing images .Change detection is used in wide variety of applications such as urban growth, land use change, deforestation, coastal change and other cumulative changes through GIS and Remote Sensing along with digital image processing techniques. More the people on the earth, greater the effect on the environment and force on the resources. The urban areas have been rapidly increased from medium to large scales. Change data can be used to update maps. It can also be used to evaluate the rates of change in certain area. This paper illuminates the outline of various states of methods available in land cover change detection along with neural network and comparison analysis of each method is conferred.

Keywords: Change Detection, GIS, Multitemporal, Remote Sensing, and Land cover Change, Neural Network.

Introduction: Change detection validate us to evaluate the gains and losses among various types of land use and land cover in a region over a period of time. Remote sensing is the technology and it has become a key tool applicable for developing and understanding the global, physical processes influencing the earth [1]. Recent evolution in the use of satellite data benefits in increasing amounts of geographical data accessible in conjunction with GIS to assist in interpretation. GIS is a homogeneous system of computer hardware and software efficient of capturing, storing, retrieving, manipulating, analyzing, and displaying geographically spatial information for the resolution of assisting phenomenon-oriented management and decision-making processes [2]. Remote sensing and GIS has increased over wide extend of applications in the fields of agriculture, environments, and homogeneous eco-environment assessment. Remote sensing data is used over a time for change detection due its high temporal resolution, extensive coverage and cost effectiveness over field surveys [3]. The satellite development improves the possibility of collecting remotely sensed facts and it offers a very good way for acquiring the records over the huge open regions. Remote sensing satellite imagery has given scientists an outstanding way to decide the reasons `for land use/land cover adjustments and the resultant outcomes because of human activity [4]. One of the most critical advantages of the satellite for staring at the earth is virtually the exchange category and tracking. The land which is covering the Earth's surface has its own uniqueness .Land is an example of the prime natural resources. Land use and land cover is a vital component in the interactions of the human activities with the environment understanding [5].

Change detection can be used as phenomenon to understand the impact of anthropological effects on natural resources, which might further assist in preparing a sustainable planning measure to protect our

environment. Change detection strategies are mainly of two types. The first approach is spectral change detection, in this approach the unit of evaluation is a pixel, a neighborhood, a multi temporal segment or a spectral class. The fundamental requirement is the accuracy of radiometric, atmospheric and geometric corrections to be performed earlier than acting the spectral change detection. The second technique is post-classification change detection. It makes use of thematic maps (categorized images) as inputs [6].A single land use map may not be adequate to identify areas where change is taking place. In order to see the changes that have taken place to the landscape, it is required to have at least two land cover maps of a region at two points in time. Consequently, the technique of 'Change Detection' appoint two or greater such thematic images belong to distinctive intervals to track the changes that have taken place in the observe region over the length of that length. This allows to evaluate which land classes are received, losses and remained the identical over the time frame.

Neural Network (NN) is a set of associated supervised learning strategies which evaluate data and recognize patterns, used for statistical classification and regression analysis. The neural-network applications we reviewed had diverse designs ranging from relatively straightforward to extremely complex, modular approaches [7]. This paper presents a neural network technique for land-cover change detection in remote-sensing imagery. Following the increasing need and the increased data availability, various techniques for the detection of changes were developed over current years. Change detection has emerged as one of the reasonably new application areas of ANN.

Analysis of Image Processing Methods for Change Detection: Analysis of Image Processing involves various methods as follows:

- **Pre-processing:** The purpose of pre-processing is an enhancement of the image data that prevent unwanted distortions or improves some image features significant for further processing.
- **Detection and extraction of an image:** Detection includes recognition of the position and other features of moving object attained from satellite. And in extraction process the detected image approximation of the route of the object in the image plane.
- **Training:** Selection of the accurate quality which finely represent the pattern.
- **Classification of image:** Image classification steps classify disclose image into predefined modules by means of appropriate scheme that evaluates the image patterns with target patterns.

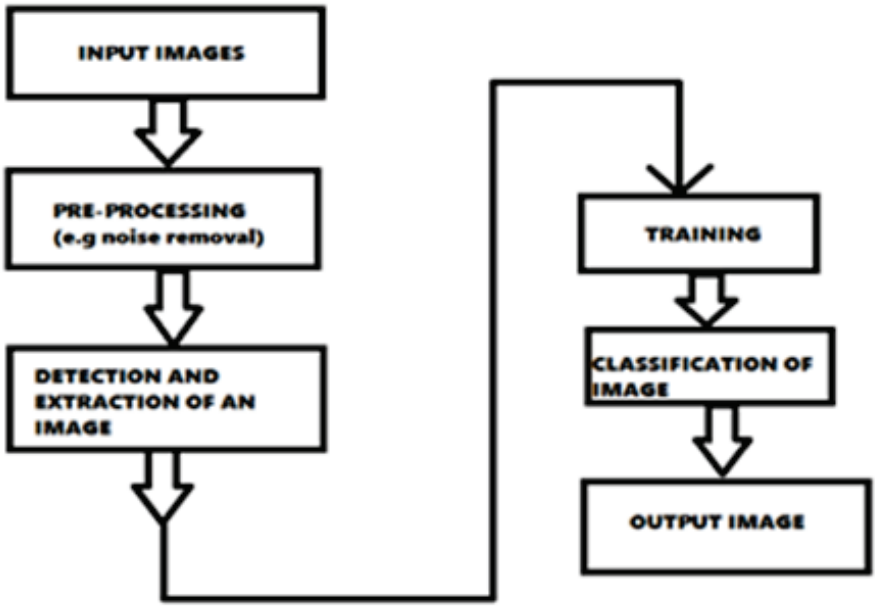

Fig1: Classification Process Flow Diagram

Change Detection Techniques:
Image Algebra To identify the changes directly, image differencing and image ratios are widely used to detect changes between multi-temporal images. Among them, image differencing (subtraction rule) is a robust and systematic method for detecting changes, and Change Vector Analysis (CVA) represents its conceptual extension with a homogenous theoretical framework [10].

Image differencing: The spatially registered multi temporal images of time t1 and t2 are subtracted pixel by pixel to produce the difference image. This method takes into account the difference of radiance values of pixels between two different dates. For each difference image, a threshold value based on standard deviation (SD) is required to portray the changed pixels from the unchanged pixels [11]. Therefore this technique is better suitable to cases as changes in radiance in the object scene is greater compared to changes due to other factors [12]. It involves subtraction of the first-date image from a second-date image, pixel by pixel.

$$D(x) = \left(I_2(x) - I_1(x)\right) \quad (1)$$

Eq (1) involves subtraction of the first-date image from a second-date image, pixel by pixel.

Image Ratioing: Image Ratioing involve the calculation of the ratio of two registered images from different dates, on a band-by-band basis. Relaying on the nature of the changes between two dates of the images, the ratio values will be significantly greater than 1 or less than 1in the changed areas. The image rationing technique is mainly used for extracting vegetation cover information [13].
Mathematically,

$$R(x) = l1(x)/l2(x) \quad (2)$$

In Eq (2), if the intensity of the reflected energy is nearly the same in each image then R(x) = 1, this indicates no change. In the area of changes, the ratio value would be significantly greater than 1 or less than 1 depending upon the nature of changes between the two dates.

Change Vector Analysis: The spectral change vector used the direction and magnitude of change from the first to the second date. The total change magnitude per pixel is enumerated by calculating the Euclidean distance between end points through n dimensional change space. CVA has the ability of analyzing change concurrently in all selected spectral bands. By applying CVA to the near infrared and short wave infrared bands, the effect of atmospheric scattering can be minimized. The accuracy of CVA depends on the image quality, geometric correction and the accuracy of threshold [14]. Change vectors is used to indicate all the image pixels, which can be seen in (3):

$$\Delta G = G - H \quad (3)$$

Where G = image pixel vector of t1 period
H = image pixel vector of t2 period

Vegetation Difference Indexing: Normalized Difference Vegetation Index (NDVI) is used for evaluate ecological variables such as vegetation cover, above ground biomass and leaf area index. The NDVI differencing method applied estimated NDVI as the normalized difference between near infrared (NIR) and visible red (RED) bands, which differentiate vegetation from other surfaces based on green vegetation chlorophyll absorption of red light for photosynthesis, and reflection of NIR wavelengths. In addition to the standardized techniques for pre-processing, threshold identification for detection of vegetation changes represents a key issue in the NDVI differencing method [15].

Thresholding: Digital change detection techniques requires the selection of a threshold value to determine the change areas. The grayscale difference map is usually converted to binary form and threshold at some pre-determined value to obtain a change/no-change classification. An automatic Thresholding algorithm is based on an iterative threshold selection. At iteration n, a new threshold Tn is established using the average of the foreground and background class means which is given by:

$$|T_n - T_{n+1}| \quad (4)$$

In Eq (4), the iterations terminates when the changes become sufficiently small

Post Classification Smoothing: Post-classification smoothing technique applies either the un-supervised or supervised classification methods. But literatures show that the supervised classification methods provide more classification accuracy than unsupervised classification methods [16]. Post-classification change detection compares pixels in a pair of classified images. Post classification change detection shows changes as a summary of the "from-to" changes of categories between the two dates. Using Post classification comparison method, the analyst can produce change maps which show a complete matrix of changes [17]. *Post processing* was to prepare the output of the final maps which resulted from the classification process (like smoothing). Both statistical and visual data were then prepared and interpreted [18].

Feature Learning and Transformation: In this category new transformation methods or selected features are employed to difference changes, mainly using a distance metric. Therefore the change feature learning method, physically meaningful features and learned change features both lead to good performance [19]. For learned features and transformation, various features or transformed feature are learned to accent the change information to detect a changed region most easily than when using the original spectral information of multi-temporal images such as in Principal Component Analysis (PCAs), Multivariate Alteration Detection (MAD), Subspace learning and Slow features.

Principal Component Analysis: Principal Component Analysis (PCA) is a mathematical technique for reducing the dimensionality of a data set. PCA was used to enhance the change information from stacked multisensor data [20]. Principal Component Analysis applies either the covariance matrix or the correlation matrix to transfer data to an uncorrelated set. The Eigen vectors of the resultant matrices are sorted in descending order where first principal component (PC) expresses most of the data variation [21]. The next largest variation is defined by the succeeding component and is independent (orthogonal) of the preceding principal component. In PCA the areas of no change are highly correlated whereas areas of change are not.

Tasseled Cap Transformation: Tasseled Cap Transformation (TCT) is used to enhance the spectral information of satellite data. In recent years, TCT has been widely used in Land cover change detection [30]. The TCT indices such as Brightness index (BI), Greenness index (GI) and Wetness index (WI) have widely been used for change detection. The TCT enhanced procedure provided better identification of the changed areas than PCA based method [22]. The TCT transform coefficients are independent of the image scenes, while PCA is dependent on the image scenes. Due to the fact the TCT based change detection method provides more accuracy than the PCA based method.

Other Advanced Methods: Change detection can be methodically represented as a statistical hypothesis test using physical models. The metric learning method is also an effective method of detecting changes using well learned distance. In addition to that canonical correlation analysis and clustering method have been proposed and found to perform well in unsupervised change detection task.

Image Classification Technique: The classification technique is to classify all pixels in a digital image into one of several land cover classes which may then be used to produce thematic maps of the land cover present in an image. Normally, multispectral data are used to perform the classification and, for sure, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization.

The objective of image classification is to perceive and depict, as a one of a kind gray level, the features happening in an image. Two primary arrangement techniques are supervised classification and unsupervised classification.

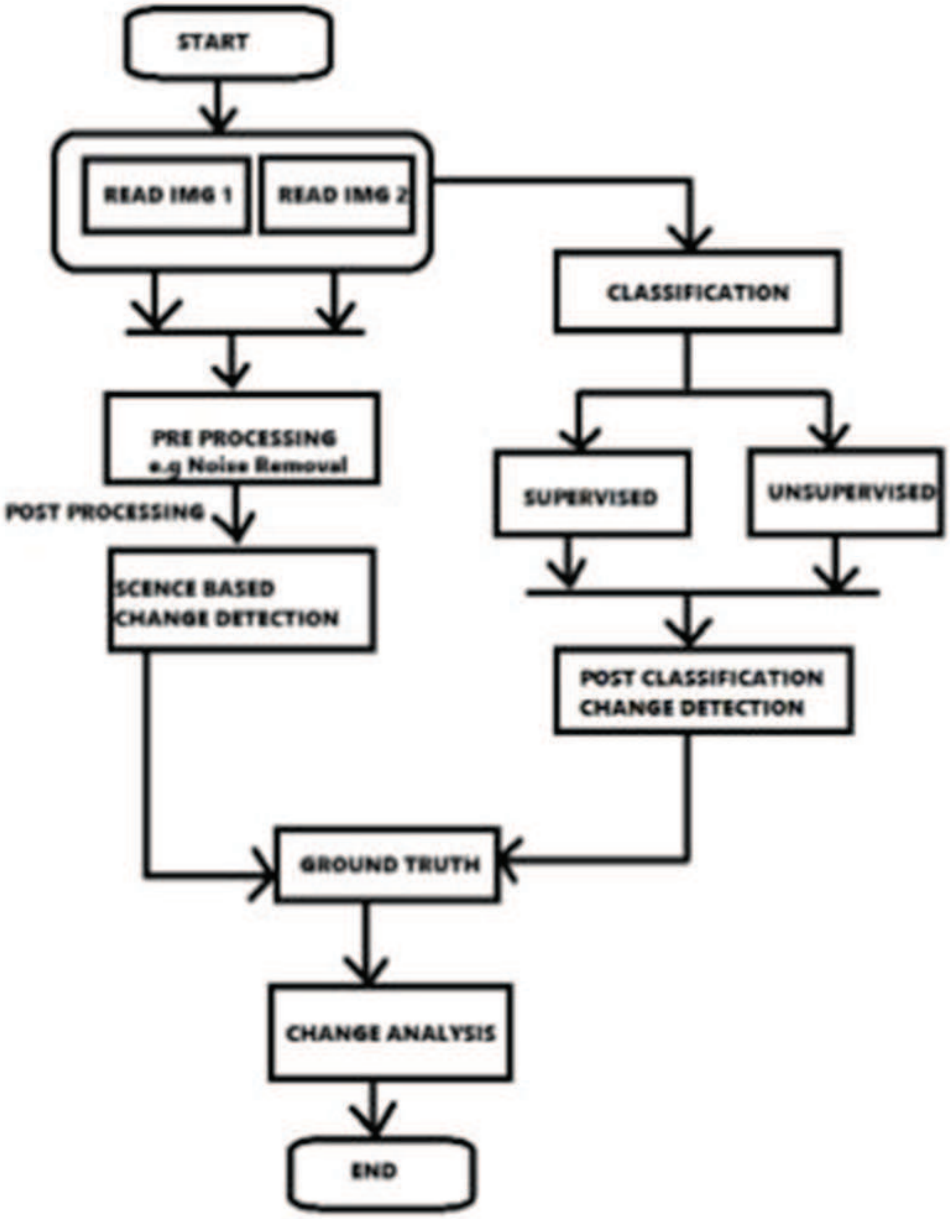

Fig 2: Flow Chart of Classification Technique

Supervised Classification Learning Algorithm: A supervised learning algorithm investigates the training data and produces an inferred task that could be utilized for mapping new cases.

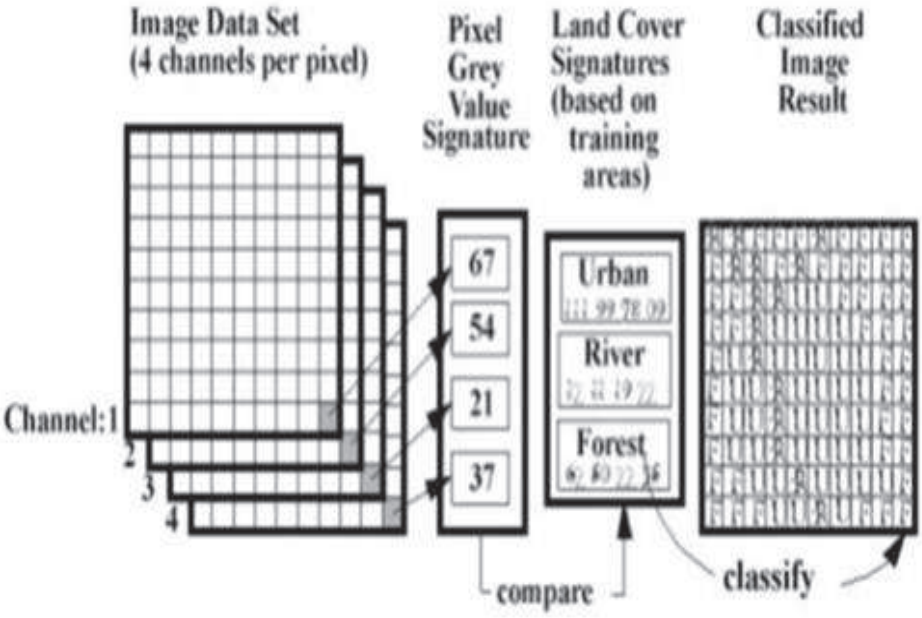

Fig 3: Phases in Supervised Classification

Maximum Likelihood Classification: Maximum likelihood Classification is a statistical decision criterion which calculates the likelihood of a pixel being in different classes conditional on the available features, and assigns the pixel to the class with the highest likelihood. Maximum Likelihood (ML) is a supervised classification method derived from the Bayes theorem, which states that the a posteriori distribution P (i|ω), i.e., the probability that a pixel with feature vector ω belongs to class i, is given by:

$$P(i|\omega) = P(\omega|i)p(i) \;/\; P(\omega) \qquad (5)$$

Where P(ω|i) is the likelihood function, P(i) is the a priori information, i.e., the probability that class i occurs in the study area and P(ω) is the probability that ω is observed. [23] Shows that the separation between mean of the classes in the decision space is to be the main factor that leads to the high classification accuracy of ML.

Advantages:

- Normally categorizes every pixel no matter how extreme it is from a class mean.
- Thresholding condition can be delivered into the classification rule to independently handle ambiguous feature vectors

Disadvantages:

- Slowest method – more computationally rigorous
- Normally distributed data presumption is not always true, in which case the results are not likely to be very accurate

Minimum Distance Classification: Minimum distance categorize information on a database file using a set of 256 possible class signature segments as distinctive through signature parameter. Each segment specified in signature, as an instance, stores signature data concerning to a particular class. The end result of the arrangement is a theme map (encodes each class with a completely unique gray level) coordinated to a unique database image channel. The selection rule in the minimum-distance-to-mean algorithm is primarily based on the relativity a few of the spectral distances among the pixel and the mean of all information classes which have been obtained from the training samples [24].

Parallelepiped Classification: The parallelepiped set of rules assigns a pixel into one of the predefined record classes in terms of its value with regards to the DN range of each class in the same band. The parallelepiped classifier makes use of the class limits and saved in each class signature to determine if a given pixel falls within the class or not. The class limits recognize the dimensions (in standard deviation units) of each side of a parallelepiped adjoining the mean of the class in feature space.

If the pixel falls within the parallelepiped, it is assigned to the class. However, if the pixel falls within more than one class, it's far positioned within the overlap class (code 255). If the pixel does no longer fall inside any class, it is assigned to the null class (code 0).The parallelepiped classifier is commonly used when speed is needed. The drawback is (in many instances) bad accuracy and a massive wide variety of pixels categorized as ties (or overlap, class 255). The main advantage is fastest method computationally and desirable for assisting decide in case you need extra training (if there are many unclassified pixels).

KNN Classifier: The k-nearest neighbors (k-NN) algorithm is a non-parametric instance-based learning strategy utilized for classification and regression, where the function is only estimated locally and all calculation is conceded until classification.

Naive Bayes: The Naive Bayes classifier takes its path over a simple however instinctive notion. It is based totally on Bayes rule of conditional probability. Naive Bayes model has made itself to be more constantly robust to infringement of a restrictive independence supposition [25]. A benefit of naive Bayes is that it only requires a small number of training data to approximate the parameters necessary for classification.

Ground Truth and classification accuracy assessment: Ground truth is done in order to observe and collect information about the actual condition on the ground at a test site and determine the relationship between remotely sensed data and the object to be observed. It is recommended to have a ground truth at the same time of data acquisition, or at least within the time that the environmental condition does not change.

Evaluating the Accuracy of A Classification: The basic idea is to compare the predicted classification (supervised or unsupervised) of each pixel with the actual classification as discovered by ground truth. Four kinds of accuracy information:

1. Nature of the errors: what kinds of information are confused?
2. Frequency of the errors: how often do they occur?
3. Magnitude of errors: how bad are they? E.g., confusing old-growth with second-growth forest is not as 'bad' an error as confusing water with forest.
4. Source of errors: why did the error occur?

Unsupervised Classification Learning Algorithm: Unsupervised classification is a way which examines large extensive type of unknown pixels and divides into some of instructions primarily based on natural groupings present inside the image values. An unsupervised learning method is a clustering approach used to find out grouping structure in a set of data [26]. Unsupervised classification is fetching an increasing number of familiarity in agencies which are worried in long phase GIS database preservation.

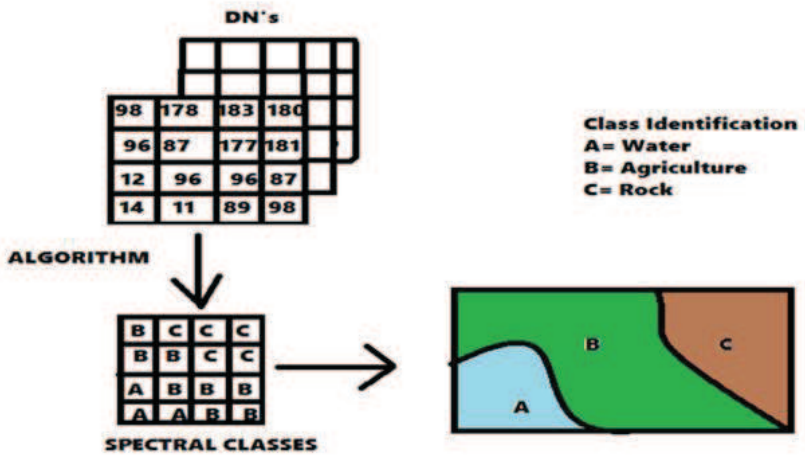

Fig 5: Phases in Unsupervised Classification

Hidden Markov Model (HMM): The hidden Markov model can be characterized as the simplest dynamic Bayesian network (DBN).HMM is closely related to an optimal nonlinear problem. In order to carry out block based classification, the image is subdivided into blocks. Then a characteristic vector is produced for each block by means of grouping statistics obtained from the block. This technique depends upon the block size. We must not choose a massive block size as this reasons crude classification. When we are selecting a small block size, only the local properties which belong to the small block are observed. Hence, the drawback is that facts approximately the surrounding areas is misplaced. HMM are of kinds 1D-HMM and 2D-HMM [27]

K-means Clustering: Clustering is a technique in which similar colors are grouped together [28]. K-means is one among the modest unsupervised learning algorithms that solve the well-known clustering problem.

Advantages:

- Fast, robust and difficult to apprehend.
- Gives best result when data set are distinct or properly separated from each other.

Disadvantages:

- The use of Exclusive Assignment - If there are tremendously overlapping data then k-means will no longer be capable to resolve that there are two clusters
- Unable to deal noisy data and outliers
- Algorithm fails for non-linear record sets.

c. ISO Data algorithm: Iterative Self-Organizing Data Analysis Technique which is a Generalization of K-Means algorithm. It consists of many user-specified parameters:

- Minimum and Maximum size of cluster
- Maximum intra-cluster variance
- Minimum separation between pairs of clusters
- Maximum and Maximum number of clusters
- Maximum number of iterations

GMM clustering: Gaussian mixture models (GMM) are frequently used for data clustering. It is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters. To identify and extract areas from the object-based difference image, a GMM-EM Thresholding technique was selected to generate the unsupervised-based difference image [29]. The Expectation-Maximization (EM) algorithm fits the GMM.

SOM algorithm: The SOM algorithm depends on unsupervised, competitive learning which offers a topology preserving mapping from the high dimensional space to map units(usually form a two-dimensional lattice and thus the mapping is from high dimensional space onto a plane). The SOM technique might be particularly helpful for reasoning dynamic oceanic processes from satellite imagery, as it assumes there is a hidden continuum of patterns [30]. The SOM can thus serve as a cluster analyzing tool of high-dimensional data. It also has the ability to generalize. Generalization ability implies that the network can perceive inputs it has never encountered earlier than.

Literature Survey:

Artificial Neural Network: A new method for remotely sensed change detection based on artificial neural networks is furnished. ANN is data driven and self-adaptive. ANN can provide universal functional approximation [31]. The neural classifiers do not require initial hypotheses on the data distribution and they are able to learn non-linear and discontinuous input data. The algorithm for an automated land-cover change-detection system was advanced and performed based on the current neural network techniques for multispectral image classification [32].Change Detection method based on neural network using back propagation training algorithm was implemented. The trained four-layered neural network was able to produce a complete categorical information about the nature of changes and detect land-cover changes with an overall accuracy of 95.6 percent for a four class classification scheme [33].The images are represented as a set of point vectors an ANN is then trained to predict the new values from the old values. The ANN is then used to predict the new values on the same

images, point where the prediction is significantly in error are deemed unusual changes. Artificial neural networks have been applied to the change detection problem, specifically using images and land use category "training data" to identify changes in land cover [34]. A Hopfield neural network technique for change detection in multi temporal images. It is a supervised change detection method. A difference image is obtained by subtracting the pixel intensity of one image from another image. Each Pixel is the difference image is identified by a neuron in the Hopfield network and is connected to all the neurons in the neighborhood. Using a threshold the pixels are segmented into two classes of pixel-changed and unchanged [35].

Probabilistic Neural Network: Supervised change detection technique for satellite images using a probabilistic neural network (PNN). The proposed method works in two phases. In the first phase a difference image is computed. The most commonly used techniques for computing the difference image such as ratio images or log ratio images degrade the performance of the algorithm in the presence of speckle noise. To overcome the above mentioned limitations the difference image in this work is computed using normalized neighborhood ratio based method. In the next phase the PNN is used to detect efficiently any change between the two images. An estimator is used by the PNN to estimate the probability density function. The ratio of two conditional probability density functions, called the likelihood ratio is computed. Finally, the log likelihood ratio test is used to classify the pixels of the difference image into changed and unchanged classes to create a change map. The change map highlights the changes that have occurred between the two input images. The proposed method was compared quantatively as well as qualitatively with other existing state of the art methods. The results showed that the proposed method outperforms the other methods [36].The PNN has proved to be quite efficient as it has fast training process an inherent parallel Structures and guaranteed optimal classification performance .The network architecture is made up of four layer of units input unit, pattern unit, summation unit and output unit. The network has an estimator for probability density function (pdf) the pdf are used to compute likelihood ratio. Log likelihood ratio test is done to assign pixel of difference image into changed and unchanged classes to create a change map.

Comparative Study of CNN and RNN: DNN is an ANN which can represent complex non-linear relationships. Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN), the two main types of DNN architectures, are widely discussed to handle various tasks. The main guideline of novel deep Convolutional Neural Networks (CNN) features based HR satellite images CD method is to construct a change detection map directly from two images using a pertained CNN. This method can exclude the limited performance of hand-crafted features [37]. A recurrent neural network (RNN), an salient component of the deep learning family, is mainly outlined to handle sequential data. [38] Relies on an improved Long Short-Term Memory (LSTM) model to acquire and record the change information of long-term sequence remote sensing data. Recurrent neural networks (RNNs), of which Long Short-Term Memory networks (LSTMs) are a popular variant, have internal memory to allow long-term dependencies to affect the output. In these networks, some intermediate operations generate values that are stored internally in the network and used as inputs to other operations in conjunction with the processing of a later input. To reduce the total number of parameters to efficiently process hyper spectral data, a modified gated recurrent unit (GRU) is adopted to construct the recurrent layer in our network [39]. Many applications and architectures of the deep learning community can be applied to the domain of earth observation for efficient, large scale data processing [40] .We found that RNNs perform well and robust in a broad range of tasks except when the task is essentially a key phrase recognition task as in some sentiment detection and question-answer matching settings. In addition, hidden size and batch size can make DNN performance vary intensely. This suggests that optimization of these two parameters is crucial to good performance of both CNNs and RNNs.

Discussion: From the reviewed literatures, we found the strength and limitations of different change detection techniques and obstacles faced in neural networks.

Strength and Limitation of Different Change Detection Techniques:

TECHNIQUES	PROS	CONS
Image Differencing	Easy method and simple to implement.	Nature of change detection is not found exactly and accuracy depends on threshold value.
Image Ratioing	The effect of sun angle and shadow may vary and topography is reduced.	Non Gaussian distribution of image makes threshold value difficult
Vegetation Index Differencing	Is appealed for both human-included and natural forest change detection	Threshold identification for detection of vegetation changes represents a major issue
Change Vector Analysis	It offers qualitative information of the direction and intensity of change. CVA are applicable to any number of spectral bands	Accuracy depends on the image quality, geometric correction and threshold.
Post Classification comparison	Provides start to end change detection result	Accuracy depends on classification of the image accuracy
Principal Component Analysis	Used to identify where the change has occurred	Difficult in producing result. Knowledge about the study area is necessary
Tasseled Cap Transformation	Data redundancy is reduced	Difficult to interrupt and label change detection

Issues in Neural Network: When developing a neural network application, it is quite common to face problems regarding how accurate the results are. The common source of these problems can be various such as: bad input selection, noisy data, and unsuitable structure, inadequate number of hidden neurons, inadequate learning rate, and bad dataset segmentation. The design of a neural network application sometimes requires a lot of patience and trial-and-error methods. There is no methodology stating specifically the number of hidden units and/or which architecture should be used, but there are references on how to properly choose these parameters. Thus a neural network performs better, either by developing its accuracy or by extending its knowledge.

Conclusion: In this paper, we have discussed about the different change detection strategies for classifying different types of images. This paper also discussed the scenarios and various image classification techniques. Neural networks are not anymore automatically seen as the best solution to any classification or regression problem, new development techniques, e.g., the recently proposed support vector machines seem easier to grasp people's eyes. This may be a new trend for the application of neural network for satellite image processing. The main advantages of the neural networks used for satellite image processing are that they are applicable to a immense variation of problems and relatively easy to implementation. Our study also discussed different scenarios for various change detection techniques as well as the advantages and disadvantages of each of them. So, this paper will help us in selecting an appropriate classification technique among all the available techniques.

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