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Change Detection using Deep Learning and Machine Learning Techniques for Multispectral Satellite Images

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Abstract: ***Change detection is used to find whether the changes happened or not between two different time periods using remote sensing images. We can use various machine learning techniques and deep learning techniques for the change detection analysis using remote sensing images. This paper mainly focused on computational and performance analysis of both techniques in the application of change detection .For each approach, we considered ten different kinds of algorithms and evaluated the performance. Moreover, in this research work, we have analyzed merits and demerits of each method which have used to change detection.***

Keywords: Convolutional neural network (CNN), Image averaging and maximization, Discrete Cosine Transform, remote sensing

I. INTRODUCTION

There is a lot of development in remote sensing technology. Everyday a lot of remotely sensed data are produced by various satellites like landsat7, landsat8 LISS III etc. Change detection is very important to discover land changes in the same area for a period of time [1]. This can be used for various applications like urban expansion, disaster management, land cover object identification etc. Synthetic aperture radar (SAR) images are produced by sending a microwave signal sensors to the ground and receives the backscattered waves from the ground which is received by the receiver [2]. A microwave beam of (0.3-30cm) is used. Convolutional neural network is part of Artificial Intelligence. It is a way of making the computers to take the decisions like human being. Convolutional neural network is an algorithm used to find patterns for a given dataset. Convolutional neural network are processed based on layers [3]. For example,if we are passing an image of car as input then the first layer identifies the dots and edges and the second layer identifies the tires, hood and other parts then, the third layer identifies the full car and give the output as car [4]. To do this the neural network has to be trained with similar images and to find the patterns in such a way that if similar pattern occurs in future it will recognize it based on the past patterns learnt. Change detection can be done using different algorithms such as k-means clustering algorithm, generic algorithm etc [5]. Convolutional neural network can be used for general purposes like road traffic condition classification or medical purposes like diagnosing automated stroke lesion segmentation or commercial purposes like horror image recognition [6]. The following table 1 illustrates the various deep learning and machine learning techniques for change detection.

II. DEEP LEARNING AND MACHINE LEARNING TECHNIQUES FOR CHANGE DETECTION

S.N	Method	Dataset	Merits	Demerits
1	A self-organizing map and deep neural network (SOMDNCD) [7]	SAR image	Exhibits a lower missed detection rate in the SAR image data set and a more ideal false alarm rate	Accuracy rate is reduced due to noise Interference
2	Kittler-Illingworth minimum-error thresholding algorithm [8]	SAR images	This increases the size of the change class which in turn improves the accuracy of the estimation of the optimum threshold	The background information of SAR images is complex, and the texture is often less obvious
3	K-Means clustering [9]	Multi temporal satellite images	Less prone to errors caused from the noise	Thicker boundaries of the resultant change map
4	Scale invariant feature transform [10]	SAR Images	More precise results and exhibits stronger robustness against speckle noise	Mathematically complicated and computationally heavy
5	Two-level clustering [11]	SAR Images	This help to discriminate the intermediate pixels, and works better for the overlap of the changed and unchanged classes than a single FCM clustering	high time complexity

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6	K-means clustering [12]	SAR Images	differencing method performs better than the single-channel intensity band ratio and the total power ratio	Difficult to predict K-Value.
7	Parallel binary particle swarm optimization [13]	multispectral image, multitemporal images	proposed approach effectively solves the change-detection problem for the small, medium and large-scale data sets.	The disadvantages of particle swarm optimization (PSO) algorithm are that it is easy to fall into local optimum in high-dimensional space and has a low convergence rate in the iterative process
8	Genetic algorithm [14]	Advanced Synthetic Aperture Radar image	The current technology in parallel computing with high-power processors makes the proposed method feasible	GA is time consuming and it is difficult for larger problems
9	The algorithm exploits the inherent multiscale structure of the dual-tree complex wavelet transform (DT-CWT) [15]	multispectral images, multitemporal images	Robustness against noise interference under various noise types and noise levels	The increase in the number of scale S will also increase the change-detection performance at the expense of yielding larger computational load
10	Convolutional neural networks [16]	DDM images	overall improved accuracy and fewer parameters in the network	Interference of the speckle noise
11	Convolutional neural network [17]	Any face images	CNN processors will have better energy efficiency	Cannot work on more computational loads
12	Convolutional neural network [18]	video surveillance data	Traffic condition classification based on convolutional neural networks and texture interpretation of the scene correctly determines LOS for almost 90% of the tested images	The images from these cameras contain a significant number of occluding vehicles which impairs the classification
13	Markov random field framework [19]	remote sensing images	Its weighting mechanism implemented at both the pixel and the image levels to handle the reliability of the results provided by each thresholding algorithm making up the considered level	The simple MV fusion rule appears more sensitive to fusion scenarios with misleading
14	Convolutional neural network (CNN), deep learning, recurrent neural network (RNN) [20]	14 TS data sets from the UCR TS repository archive	This can be applied to a large variety of TSC tasks across different domains	The accuracy of unbalanced and multiclass dataset might not be sufficient for calculating its performance
15	Artificial intelligence, convolutional neural network, recurrent neural network [21]		This proposed network model is more accurate and efficient in classifying blood cell images	The classification of a single cell image takes about 3.8 seconds, which is clinically too slow so it needs good hardware resources
16	Deep learning, stroke lesion segmentation, residual network (ResNet), convolutional neural network (CNN), fully convolutional network (FCN) [22]	A public data set, i.e., ISLES2015-SISS	it presents very low false negatives	This research did not include detection of hemorrhagic transformation, which is a complication of ischemic stroke
17	Deep neural network [23]	JPEG2000 and optical space-borne image	less detection time and achieves higher detection accuracy	Might not give same accuracy for all types of images
18	Convolutional neural networks (CNNs), deformable convolution [24]	Hyperspectral image (HIS)	The experimental results demonstrate that DHCNet performs better than several well-known HSI classification	Thicker boundaries of the resultant change map
19	Learning algorithm [25]	Two sets of test images, the first for the singlescale case and the second for the multiscale case	This algorithm is able to accurately detect objects in complex images	multiscale detection problem is clearly harder than the single-scale one
20	Digital surface model (DSM) generation, dynamic programming [26]	satellite stereoscopic images	Better compared to the classical visual image analysis	The present processing flow cannot be applied

Table 1: Deep learning and machine learning techniques for Change detection

III. RESULT ANALYSIS

In the side of deep learning, we considered, convolutional neural network (CNN) , recurrent neural network (RNN), Faster RNN, deep belief network (DBN) and stacked auto encoder (SAE).

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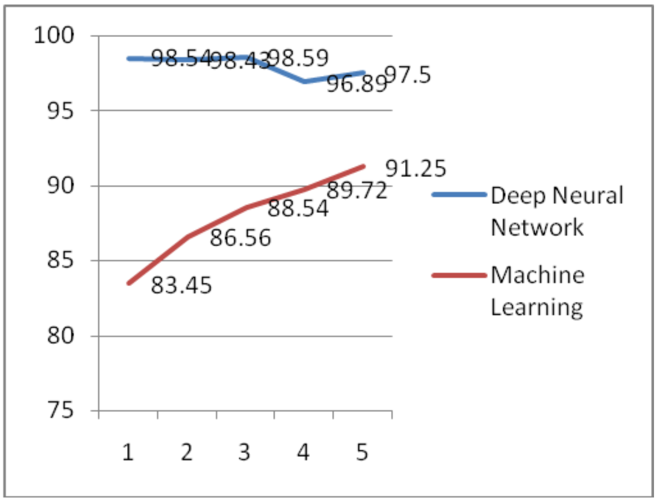
In the side if machine learning, we considered, back propagation(BP) algorithm, K-means clustering (K-means), fuzzy k-means clustering, C-means clustering and support vector machine (SVM). The main problem we found with images used for change detection is the noise interference due to this the accuracy of the output is reduced. Most of the change detection was done with multitemporal images and Multispectral images. The algorithms used for finding change detection is Deep neural network (DNN), K-means clustering, Kittler-Illingworth minimum-error thresholding algorithm, Two-level clustering, parallel binary particle swam optimization, generic algorithm etc. In deep neural network, they used around 50 hidden layers so the missed detection rate is lower. In supervised nonparametric technique based on the compound classification rule the accuracy rate was more than performance oriented congestion control and can still increase the accuracy. By using k-means clustering the errors occurring due to noise can be reduced but the foundries in the change map are thick so that accuracy is reduced. Change detection using generic algorithm can be used but it needs high processing speed and the method is time consuming and it's also not suitable for lager problems. The convolutional neural network can be used to find Sea Ice Sensing from GNSS-R Data the data set used is DMM images but the interference of speckle noise is high. Multi-Scale Deep Reinforcement Learning for Real-Time 3D-Landmark Detection in multispectral images can also be done using deep learning doing so they were able to increase the accuracy rate by 20%. Table 3 illustrates the Classification accuracy analysis of deep learning networks vs machine learning algorithms.

The sample data set is first feed to the neural network in Wheel Defect Detection. With Machine Learning different types of defect is loaded as data set and the pattern is reorganized by the neural network based on the pattern that we got from the given dataset. This Compressed-Domain Ship Detection on Space borne Optical Image the deep neural network is used to achieve less detection time with high accuracy but this cannot give the same accuracy for all kinds of images. It can give more accurate results for optical Space borne images. The main cause for reduction in accuracy of the change detection in various algorithms is because of the impacts caused due to speckle noise. The accuracy of an the algorithms vary from one type of input data images to another type of input data image, i.e the accuracy of algorithms may vary for different satellite images. When compared to machine learning algorithms, deep learning algorithms produced good results.



IV. CONCLUSSION

Change detection using multispectral images is very challenging task. To identify the changes from multispectral images we used deep learning algorithms and machine learning algorithms. While can be further improved by predicting the defect prior. .Multi-instance learning is done to recognize the pattern horror image reorganization will identify the image based on the dataset we gave as input.

In using machine learning algorithms, feature extraction phase is needed before find out the change detection. Feature extraction phase is used to boost up the accuracy of multispectral images. But, while using deep learning algorithms, separate feature extraction phase is not needed. Classification accuracy is based on which algorithms used to identify the changes and the also based on the resolution of the images. We have concluded that, deep learning algorithms produced better accuracy than machine learning techniques.

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