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Automatic Urban Change Detection using LANDSAT-8 Satellite Images and Deep Learning Techniques in Australian Capital Territory (ACT), Australia

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Abstract:

The Remote Sensing based Satellite data is useful as a very powerful tools for providing a complete information for an accurate urban area monitoring. Identifying the urban change detection is a main part of professional urban drafting, regional based urban development in fraction of low cost effective along with less time duration compared to common methods (e.g. manually field survey report, Aerial Imagery etc.). The main goal of the proposed work is to monitoring various changes in features on the complete surface of earth of various pixel resolution can be carried out by low-cost remote sensing-based LANDSAT-8 satellite images. The urban change detection is examining the various changes in urban area between two periods: 1) Baseline period 2) More recent period. In the previously, the classical change detection (CD-Algorithm) is inaccurately identifying both the spatial information and various scale variations within satellite images. To overcome the problem, the present research work introduces an advanced Deep Learning based novel Change Detection (Bitemporal_CD) technique that accurately extracts complete spatial information at various level of scales variations to simply address both issues. The new proposed model is based on Multi Scale and Multi Depth (MSMD) approach deep neural network that generates all binary information change based map that simply integrates with complete information of different sizes of patches at various decision parameter. It is used LANDSAT-8 satellites images originally from Australian Capital Territory (ACT), Suburban Nicholls, and District: Gungahlin- Australia, because total area of the ACT is 2,351.7 km2 of which 61% area is hilly or complete mountainous. The proposed advanced deep learning model is estimated in comparison with both Bi_Temporal Change Vector Analysis (Bi_Temporal CVA) and Support-based Vector Machine (SVM). On the basis of Deep learning change detection results, our proposed model shows a notable advancement in the performance of Cohen's_kappa coefficient (KC) compared to both SVM as well as Bi_Temporal CVA, with high increases of approximately 12.87% and 30.37% individually. Finally, the proposed Multi Scale and Multi Depth approach deep neural network model performs superior in detecting various changes including across all level of metrics with high accuracy.

Keywords: Multi scale and Multi depth Network, Bitemporal_Change Vector Analysis, Support Vector Analysis, Remote Sensing satellite images.

1. Introduction:

In Remote Sensing technology, the Change Detection method (CD) is an important process of effectively identifying changes from a pair of satellite images of geographical coverage area at different date and time zones. Accordingly, the change detection method is arrived as very powerful as well as primary task in remote sensing-based satellite images community with present real time world applications includes as land usage and land covering monitoring (LULC), remote sensing for agricultural, disaster assessment and management- flooding, wildfire, earthquake etc [1]. The Vision based Transformer (VT) is significant component that simply learning of spatio_temporal based representation but that includes huge computation issue, mainly for high quality of resolution satellite images. The designing of macro architectures is still lacking integrating with these vision transformer components specially for urban change detection related tasks [2]. The Field-based manually surveys are primally method of change detection but they are loaded with various serious drawbacks such as time-consuming process, require technical ability of human power for fieldwork, limitations of geographics area coverage as well as multi temporal based satellite images that provide high cost effective and effective approach to accurately monitoring various changes in the earth's area [3]. L. Castellana et al. [4] studied a novel approach of change detection, named Transition based Driven (TD)– Post Classification level of Comparison (PCC) based on combination of both the supervised algorithms along with and unsupervised algorithms. The advanced TD-PCC method is based on the class transition support matrix to accurate correction of change produced by an advanced supervised based PCC method as well as a class transition matrix both are automatically obtained data from simply an unsupervised based effective change detection technique. Prabuddh Kumar Mishra et al. [5] studied the change detection of land usage and land coverage in Rani Khola watershed of state of Sikkim Eastern Himalaya, using supervised classification based on advanced maximum Likelihood classifier from LANDSAT-5 satellite images with an advanced Thematic based Mapper (TM) and remote sensing Sentinel type_2A (13 spectral band) multispectral instrument (MSI) for the periods 1988 to 2017. Nishant Mehra et al. [6] integrated Artificial Neural Network (ANN) with a Cellular Automata (CA) for predicated land usage and land coverage maps for periods of 2025 and 2040. The ANN_CA model is included six important factors, the four factors were based on socio economic parameters such as roads, centre of city, built-up coverage areas and streams: while remaining two factors were based on geospatial data parameters such as slope and elevation. There all six factors' combinations performed the highest level of accuracy of 87.84% in ANN_CA model. Bipin Shah et al. [7] developed a new framework based on change detection (CD) algorithm of machine learning with combination of advanced Particle Swarm Optimization (PSO) and new approach of Support Vector Machines (SVM) which provides expressive improvement in overall accuracy. Sibo Yu et al. [8] devolved a framework based on Multilevel Feature based on Cross Fusion technique (Multilevel_FCF) with new approach of 3D_CNNs technique for remote sensing satellite images for change detection. Primally, the change detection (CD) method in remote sensing satellite imagery challenges due to various complex structure of similar objects as well as different time zones and various locations. The Convolutional based neural networks (CNNs) have presented high performance in change detection (CD) by effectively extracted semantic level of features. The traditional approach of 2D-CNN$_s$ method may huge struggle to extract the deep features from specially multitemporal satellite images. Author Gong, M. et al. [9] introduced the advanced remote sensing-based satellite images change detection technique that mainly combines with 2D-CNNs and Principal Components Analysis (PCA) to accurately enhance remote sensing satellite images change detection performance.

The main aim of our research study is improved the high accuracy along with exhaustiveness of urban change detection by effectively the extraction of spatial spectral information and predominant the limitations of usual change detection (CD) methods. The research study is introduced a new MSMD_CNN model-based change detection method that considers the high level of detailed information. The overall performance of the proposed MSMD_CNNs model is accurately evaluated against both Bitemporal_CVA and Support Vector Analysis (SVM) algorithms. Comparatively analysis with CVA and SVM, the proposed method MSMD_CNNs is excellence and provide high reliability and accuracy.

2. Methodology:

In our research study, the proposed MSMD_CNN CD method is compared with two advanced CD classical methods: 1) The Bi_Temporal Change Vector Analysis (Bi_Temporal CVA) and 2) Support Vector Machine (SVM). The working flow of research study is being shown in figure:01.

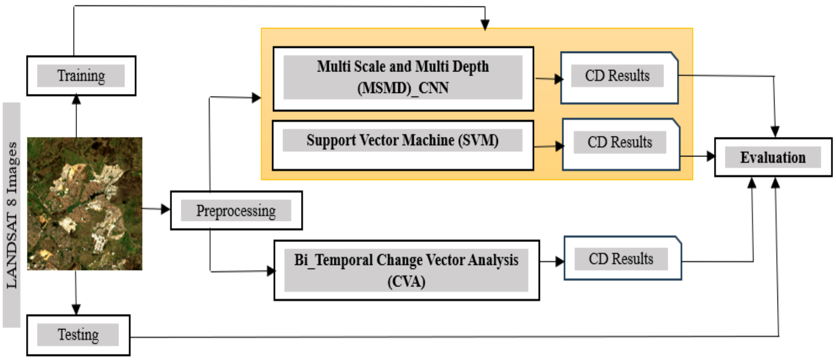

Figure:01 The working flow of Research Study

Figure:01 illustrates the primary steps of urban change detection from remote remote sensing satellite images. The research work is conducted following analysis:

1) First step to load the LANDSAT-8 satellite data over the area of city / region of interest (ROI)
2) Collected of Testing and Training Samples
3) Apply Pre-processing method
4) Apply Proposed MSMD_CNN with Bi_Temporal CVA and SVM CD methods
5) Change maps are generated by using MSMS_CNN, Bi_Temporal CVM and SVM
6) Finally, binary generated change maps are accurately evaluated and compared.

2.1) Bitemporal _Change Vector Analysis (CVA):

The advanced Change Vector Analysis (CVA) was firstly introduced by Malila in 1980 and implemented for forest change detection with LANDSAT satellite images. The necessarily to monitor a complete earth's surface over a range of both spatial scale and temporal scale are fundamental in Ecosystems Management, planning, effective action plan with implementation of various strategies. The Change Vector Analysis (CVA) is a method of change detection (CD) that primary based on Bi_Temporal method that used change of magnitude and determine both length with change of direction between two input (spectral) images at different times in Figure 02.

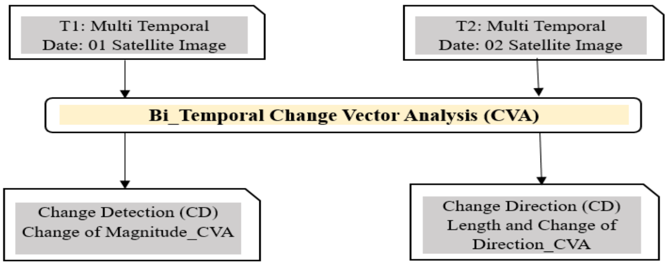

Figure: 02 Basic workflow of the Bitemporal_Change Vector Analysis (Bi_CVA)

The following equation (1) is applied to calculated the magnitude of change vector in images of various regions in which transformed data is represented by "**Δ** H" that simply lies between two different multitemporal approach image T1 and image T2 (T1: 2014 and T2:2020) captured for given pixel by Y= (y1, y2, y3,…..yi) T1 and X=(x1,x2,x3,…xi) T2 respectively [10].

$$|\Delta H| = \sqrt{(x_1 - y_1)^2 + \cdots + (x_i - y_i)^2}. \qquad (1)$$

Where "i" indicates the number of bands in data /imagery.

2.2) Support Vector Machine (SVM):

The Support Vector Machine (SVM) is fully based on theory of "Statistical Learning" that used supervised based machine learning algorithm. Nowadays, the advanced Support Vector Machine (SVM) is very popular algorithm of machine-based learning and most commonly used in advanced remote sensing based multi temporal satellite image classification with a higher accuracy. In the Supervised learning algorithms, a machine is simply trained rather of programmed using a number of training set as an example of both input and output pairs. The primary aim of training is to simply determine a function which best result that simply describes the good relation between the inputs as well as outputs.

In generally, any type of learning problem in most of statistical learning theory always will lead to a proper solution of the type:

$$f(x) = \sum_{i=1}^{l} c_i K(x, x_i) \qquad (2)$$

In the above equation (1), where xi, "i" represents the i=1,2,3……, l are the inputs, "K" is a Kernal that represent a symmetric definite function and "ci" is represent set of parameters to be simply determined from given samples. Advanced Support Vector Machine (SVM) uses both classification and regression to map points in higher dimensional space that simply separate the two different categories of points.

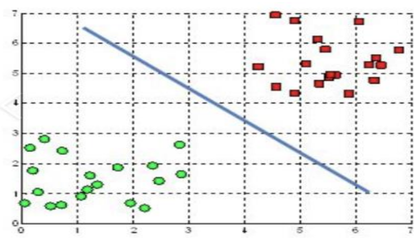

Figure:03 Hyperplane with separated points.

In the figure:03 shows an example of two different categories of points (red and green) are separated by an optimal hyperplane. The two categories of points (red and green) are located closed to the hyperplane which are called as "Support Vectors" (SV) machine. Each side of plane can be more than one support vector (SV). In the remote sensing, the SVM has best proven to be advanced in both heterogeneous and homogeneous land use and land cover features [12].

2.3) Multi Scale and Multi Depth (MSMD) CNN:

Recently, Convolutional Neural Networks (CNNs) are most widely used in new approach of remote sensing-based satellite imagery applications. Sometimes, the Remote Sensing satellite images are more complex, the huge different variation of scales and complex surrounding will effectively affect the performance of the detection. As Previously, some deep learning classification algorithms are completely depended on spatial based spectral information and feature extraction. The Single Scale CNNs ignore both spatial based spectral information and some detailed features during features extraction and resulting the overall performance of the detection methods are poor. To overcome, this problem, the proposed method is based on Multi scale and Multi Depth Convolutional Neural Networks (MSMD_CNN). The Multi scale and Multi Depth CNNs is an effectively work with a large-scale variation. Firstly, the dataset is divided into two type of pixel module, and then two or more different channel are used for various feature extraction. In Multi scale and Multi Depth CNNs, utilize different sizes of convolution kernels to better extract the spatial spectral detailed information and then combined together for final classification [13][14].

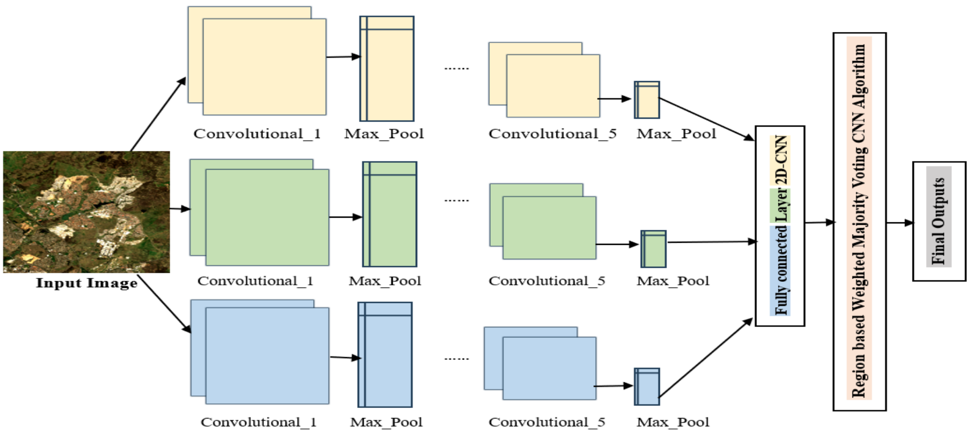

Figure:04 The proposed MSMD CNN architecture

Figure: 04, shows the MSMD_CNNs include multiple layers along with convolutional, ReLU, Max_Pool, Fusion and fully connected layers.

The proposed system involves the 2D CNN are used to extract spatial spectral information, respectively with various inputs to simply classify the bitemporal based LANDSAT-8 satellite images along with region of weighted based majority voting CNN algorithm is integrated with final results. The patch sizes [3×3, 7×7, and 10×10] are used as inputs, the kernel size is 3×3 for sequence of the filters is presented in [64,128,256] order.

3) Experimental Result:

3.1) Research Study Area and datasets:

In research study, the LANDSAT-8 remote sensing satellite-based images are used for effectively evaluated of the proposed method in various changes in region of Australian Capital Territory (ACT) area. Australian Capital Territory is mainly situated in the province of Australia, with a longitude of

149.1210 and a latitude of -35.1836. The complete area of the Australian Capital Territory is over 2,400 km^2. The Australian Capital Territory is surrounded by Ngunnawal, Palmerston and New South Wales. The Australian Capital Territory extend 89 km from north to south zone along with only 31km from west to east zone. The landscape around Ngunnawal, Palmerston are made up of hill areas, huge mountains and rugged plains, as well as lot of trees.

Figure:05 The location of the Australian Capital Territory (ACT) (Image is acquired from Google satellite earth engine).

3.2) Result Analysis:

The landsat-8 satellite images were acquired from a powerful platform of the Google Earth Engine on year of 2014 and year of 2020. The geographic region of the Australian Capital Territory (ACT) studied area is detailed in figure 06.

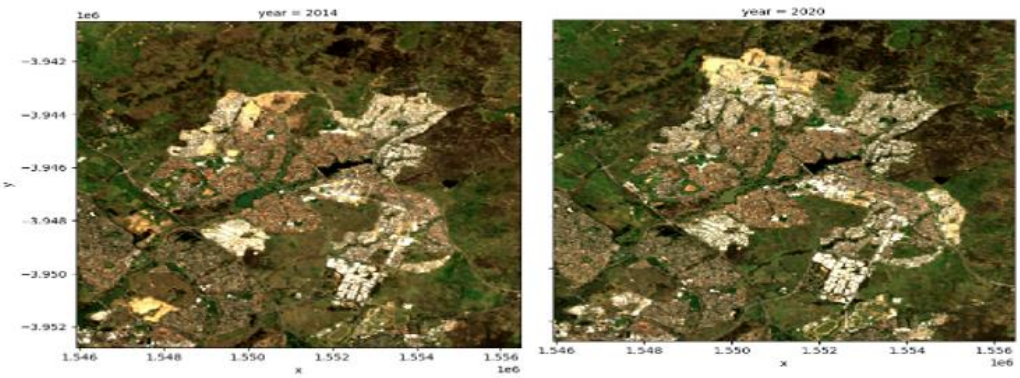

Figure: 06 Google earth engine year of 2024 and year of 2020

3.2.1) Calculate Impervious Surfaces (ISs) Indices:

In this research study, the proposed method aims to mainly analyse the relevant as well as performance of various impervious surface (IS) four Indices methods such as: 1) MNDWI 2) SWIR_DIFF 3) ALPHA and 4) ENDISI using remote sensing LANDSAT-8 images in different study regions.

1) Modified_Normalized Difference Water Index (MNDWI):

The Modified_Normalized Difference Water Index (MNDWI) accurately differentiates between open water features and urban area in remote sensing satellite images. This MNDWI methods uses the Visible GREEN and SWIR_1 spectral bands.

$$\text{MNDWI} = \frac{(\text{Visible GREEN} - \text{SWIR\_1})}{(\text{Visible GREEN} + \text{SWIR\_1})} \tag{3}$$

Visible GREEN= GREEN band of pixel values

SWIR_1= Short-Wave Infrared Band_1 of pixel values

2) Short Wave Infrared Bands _Diff (SWIR_Diff):

The Short-wave infrared bands _Diff (SWIR_DIFF) are effectively distinguishing water cloud and ice could as well as snow and ice which most appear white in visible light.

$$\text{SWIR\_Diff}= \frac{\text{SWIR\_1}}{\text{SWIR\_2}} \tag{4}$$

3) Alpha:

$$\text{Alpha}= \frac{2*\text{mean (BLUE)}}{\text{mean }(swir_{d}iff) + \text{mean (MNDWI}^{2})} \tag{5}$$

4) Enhanced Normalized Difference Impervious Surfaces Index (ENDISI):

The Enhanced normalized difference impervious surfaces index (ENDISI) is simply differentiated between two surfaces such as: 1) Impervious surfaces (ISs) and Natural Surfaces (NSs).

$$\text{ENDISI}= \frac{\text{BLUE-alpha}*(swir_{d}iff + \text{MNDWI}^{2})}{\text{BLUE+alpha}*(swir_{d}iff + \text{MNDWI}^{2})} \tag{6}$$

To find a major differences between both the impervious based surfaces (ISs) and natural surfaces (NSs), the ENDISI is primary selected the BLUE (color) band as an Impervious surfaces (ISs) enhancement factor as well as simply ratio of Band SWIR_1 to Band SWIR_2 along with MNDWI as obstruction.

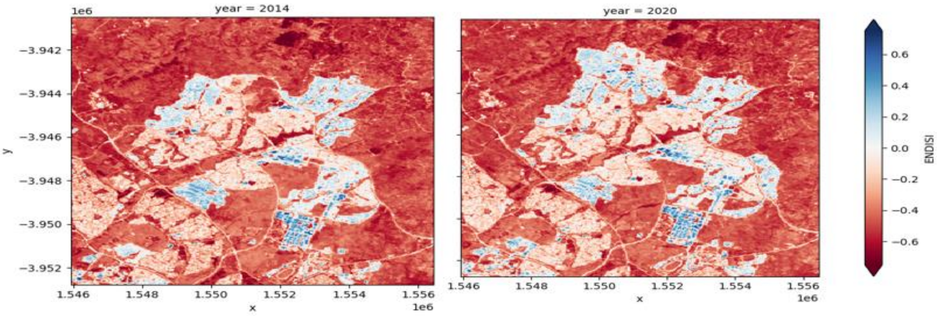

Figure: 07 ENDISI calculation (MNDWI, SWIR_Diff and ALPHA)

3.2.2) Apply Threshold:

The change detection image analysis is one of primary step in comparison of remote sensing multitemporal images. The main aim of change detection image analysis is to simply generate a change_map image that mostly increases the contrast level between both changed area and unchanged area. The change_map has been generated by thresholding with the Otsu's method (threshold= -0.1) [11].

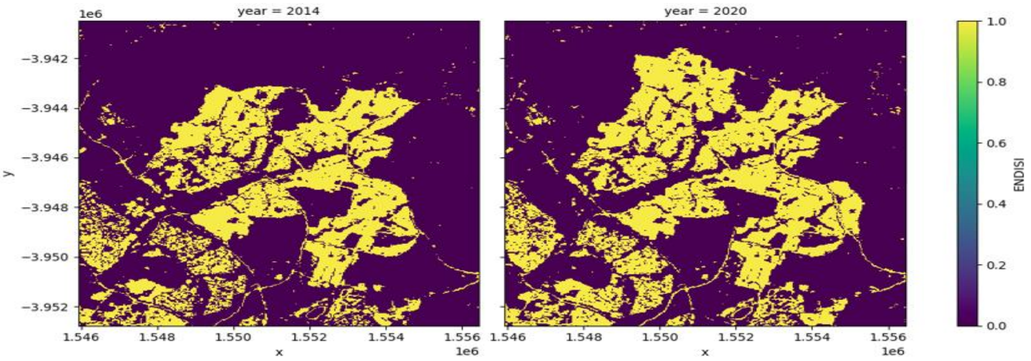

Figure:08 Calculated urban extent with threshold (Ostu Method)

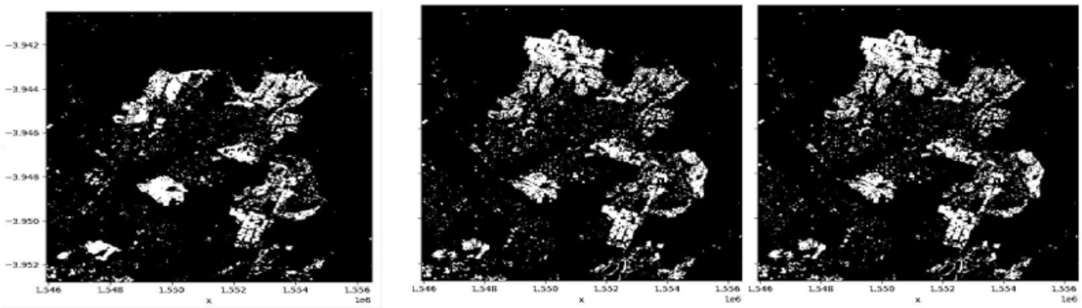

Figure 09: Binary map is generated a) CVA b) SVM c) Proposed MSMD_CNN

In above Figure 09: shown the binary based change maps are generated by the Bitemporal_CVA, SVM and proposed MSMD_CNN technique. The Bitemporal CVA that inaccurately identified most areas as changes. The proposed MSMD_CNN and SVM techniques have been superior performance compare to Bitemporal_CVA in detecting area change.

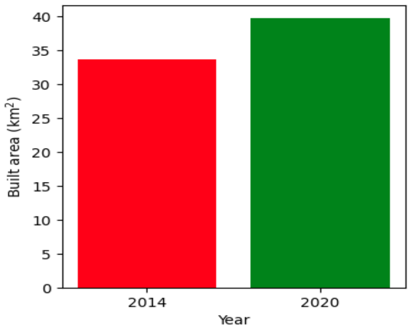

Figure:10 Plotted change in urban extent

In figure 10, the area of urban extent in 2014 is 33.641999999999996 km^2 (Red color) and the total area of urban extent in 2020 is 39.7296 km^2 (Green color).

The figure 10 shows, the confusion-based matrices of Binary change_Map that simply comparing with the ground truth data value. The based-on confusion-based matrices, it is show that the Bitemporal_CVA algorithm misidentified 191 pixels, where SVM and proposed MSMD_CNN misidentified 133 and 51 pixels, respectively.

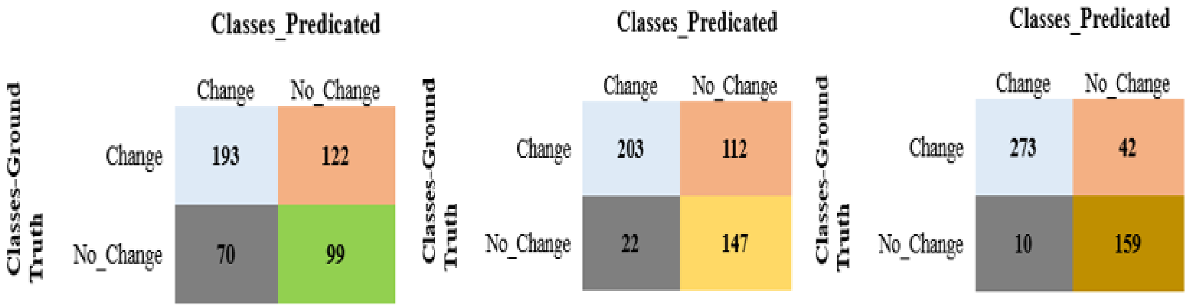

Figure 11: a) Confusion Matrices_CVA b) Confusion Matrices_SVM c) Confusion Matrices_MSMD_CNN

These numbers in the confusion matrices with CVA, SVM and proposed MSMD_CNN shows the overall performance of CVA, SVM and MSMD_CNN algorithm based on overall classification accuracy. Additionally, all evaluation criteria, the Precision Value_(P), Recall Rate_(R), F1 Score_(F1), Overall Accuracy_(OA) and Kappa Coefficient_(KC), are used to conducted an extensive along with perceptible assessment of results.

Table 1: Accuracy based Assessment of Bitemporal_CVA in change Detection (CD).

Classes	**Bitemporal_CVA**		
	Precison_(P)	**Recall Rate_(R)**	**F1 Score_(F1)**
Change	0.7457	0.6235	0.6791
No_Change	0.4576	0.5969	0.5179
KC (%)		49.66	
OA (%)		61.42	

Table 2: Accuracy based Assessment of SVM in change Detection (CD).

Classes	**SVM**		
	Precison_(P)	**Recall Rate_(R)**	**F1 Score_(F1)**
Change	0.9159	0.6555	0.7638
No_Change	0.5782	0.8844	0.6988
KC (%)		67.17	
OA (%)		73.51	

Table 3: Accuracy Assessment of proposed MSMD_CNN in change Detection (CD).

Classes	**Proposed MSMD_CNN**		
	Precison_(P)	**Recall Rate_(R)**	**F1 Score_(F1)**
Change	**0.9781**	**0.8791**	**0.9259**
No_Change	**0.8041**	**0.9562**	**0.8635**
KC (%)		**79.03**	
OA (%)		**90.59**	

In the table 3, the proposed MSMD_CNN in change detection (CD) approach determines a Precison_(P) of 0.9781, Recall Rate_(R) of 90.59 and F1 Score_(F1) of 0.8635 in detecting changes that representing the highest precision value (P), Recall score (R) and F1 Score (F1) among Bitemporal_CVA and SVM methods. The Bitemporal_CVA exhibits the poor performance with Precison_(P) value of 0.4576, Recall Rate_(R) of 61.42 and F1 Score_(F1) of 0.5179. Finally, when considering all criteria, it come that the proposed MSMD_CNN network model outperforms the good performance compared to the other Bitemporal_CVA and SVM methods.

4. Conclusions:

The advancement in remote sensing satellite images technologies has huge improved an accurate monitoring of environmental diversity mainly in urban areas. Previously, the classical methods cannot easily integrate with spatial based spectral information along with some detailed features, limiting their overall performance of detected changes in the urban areas. The advanced Deep Learning based techniques that accurately extract both spatial based spectral information and detailed features during feature extraction offer high accuracy in urban area change detection. In this research study, an advanced deep learning-based change detection (CD) approach to previous classical change detection methods, namely Bitemporal_CVA and SVM to detect area changes in Australian Capital Territory (ACT) in Ngunnawal, Palmerston and New South Wales cities. It has been concluded that Bitemporal_CVA has achieved F1_Score 0.5179 and SVM technique has achieved F1_Score 0.6988 overall accuracy assessment. On the other hand, the proposed MSMD_CNN has achieved F1_Score 0.8635 overall accuracy assessment. Based on different evaluation criteria of the results, the Bitemporal_CVA has the poor performance in the change detection (CD). The supervised machine SVM algorithm can enhance the accuracy, the proposed MSMD_CNN resulted in an exceptional 18% increase in the overall accuracy of the MSMD_CNN binary change map.

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