
An Approach Automatic Change Detection Method for Satellite Images using Deep CNN

Dr. Monika D. Rokade, Dhumal Bhagyashri, Ghegade Trupti, Dr. Sunil S. Khatal
Assistant Professor, Department of Computer Engineering, SPCOE, Pune, India
Student of Department of Computer Engineering,
Sharadchandra Pawar College of Engineering, Dumbarwadi (Otur), Tal. Junnar, Dist. Pune

Abstract: In geoscience, Change Detection (CD) is a useful method for analysing land surface changes using data from Earth observation and for uncovering links between human activities and environmental phenomena. In this work, a supervised Deep Learning (DL)-based change detection technique was developed to generate an accurate change map, as improving the quality of the binary CD map is a crucial issue in remote sensing images. Due to its strong performance and promise in the realms of pattern recognition and nonlinear problem modelling, DL is gaining traction as a means of overcoming the CD issue using multi temporal remote sensing imageries. Using DL methods, specifically Convolutional Neural Networks (CNN), may help divide environmental changes into two classes: with and without human intervention. To identify the same shift between two SAR pictures, we suggested a Deep CNN in this study. To classify the changes and properties of RSI images, a CNN is employed for supervised classification. A differential picture is generated using the information supplied by the CNN's convolution layers without prior training on objective difference images. Research has made use of the NASA satellite picture collection. Therefore, the change detection approach may be implemented in a supervised manner, making it suitable for usage with any classification algorithm or CNN that has already been pre-trained.

Keywords: Convolutional neural network, semantic segmentation, image processing, Change detection, Supervised learning.

INTRODUCTION

Understanding natural assets and manmade buildings is critical for commercial and military sites, making change detection useful. The problem of tracking changes over time in several satellite images of the same location is at the heart of this study. Post-classification analysis and difference image analysis are the two primary methods used by existing change detection methods [2]. These methods are often time-consuming and labour-intensive due to the high resolution of satellite photos. Two images of the same event taken at different times might be compared after categorization using post-classification assessment [1]. A high level of accuracy is required in the classification since errors in categorizing might occur with any of the two images. A distinct image emerges from the second approach, comparative analysis, which is what was applied for this study. These pictures were made to show how the same topic may seem different depending on when it was photographed. Different methods of picture analysis are then used to ascertain the changes' nature.

The results of the change detection process are affected by the quality of the produced images. When processing satellite images, techniques like radiometric correction [2] are often employed to counteract the negative impact of atmospheric refraction on the image's spectral reflectance. A number of methods, including spectral interpolation [3], rationing [4], and textural rationing [4], are employed to generate visually different images. In this study, enticing and varied visuals were created using a deep neural network (CNN) [5]. In the past, deep neural networks (DNNs) have been successfully used to help discover and emphasize differences while avoiding some of the drawbacks of conventional methods [6]. In this study, we provide a novel approach to detecting and labeling transitions by using convolutional neural networks (CNNs) educated in the art of semantic segmentation. The proposed method is novel in that it generates the alternative designs via unsupervised change of extracted features at different levels of a trained CNN, which makes it easier to learn across related solutions.

The major objective of this study is to test how well a trained CNN can use feature maps derived from two similar but time-separated images to produce a novel image. The most up-to-date AI studies have either been wide-ranging evaluations of the development of AI algorithms [11] or RS implementation reviews for a specific hot sector [12]. The authors of [13] focused their attention on in-depth theoretical strategies, methods, and problems in the RS industry. These review articles focus on the theoretical and practical applications of AI in RS. There is still a need for a thorough evaluation of AI algorithms used for co data change detection in RS data. In this research, we take a close look at how artificial intelligence tools are used in remotely sensed processing, or RS. It focuses on cutting-edge AI change detection methods, multi-temporal data applications, and related issues. Our main contributions are as follows:

The most common implementation strategies are summarized, and the process for implementing AI-based activity identification is outlined to help novices get a handle on the material.

- We examine optical RS information, SAR data, street-view images, and mixed heterogeneous data, all of which are used for AI-based activity identification.
- We describe their broad concepts in a practical way by methodically examining and analyzing the procedure of AI-based variation detection techniques, which may help to create change methods for detecting in the future;
- We provide a collection of open resources with annotations that may be used as training and evaluation standards for AI models in associated development detection investigations.
- To address the problem of insufficient training data in practical applications, we also look at the unsupervised methods currently used in AI-based activity identification.
- Fourth, we discuss the most popular AI networks for change detection. We examine the most popular AI networks for use in activity identification, and we analyze their applicability to help with step
- We outline and explore the problems and potential of AI for activity recognition from three different perspectives, namely heterogeneous large data processing, unsupervised AI, and AI dependability, and provide a valuable resource for future study by outlining and exploring these issues and potential from these angles of investigation.

LITERATURE SURVEY

Surveillance of the land is a multifaceted process, ever evolving as a result of both natural and anthropogenic factors. Accelerating environmental change is a byproduct of the expanding industrial and technological sectors, which has led to an over reliance on data [1]. Studies of urban expansion, environmental radii, agricultural monitoring on farmed land, risk assessment after natural disasters, and other aspects of environmental change are greatly aided by satellite imagery [2]. Land uses in urban areas are more varied and subject to rapid change and adaptation than in more rural settings. Remote sensing techniques, also known as detection approaches, are used to track and assess these shifts in real time and without the need for costly and time-consuming field activities.

Maps depicting land use, urban coverage, and other types of multi-time inquiry may benefit greatly from change detection. Non-automatic, visually inferior features are used by most existing change detection systems. More recently, artificial neural networks have been utilized to extract data directly from input images because of their increased robustness and abstraction. Due to the inefficiency of manual change detection, this study introduces a deep learning-based way to creating the change map. The goal of this system [3] is to give a binary label to every pixel pair or sequence of geo-referenced images captured at different times in the same region. One of the most well-known and cutting-edge methods of machine learning in recent years is the use of deep learning algorithms. It's proof of their extraordinary abilities and potential. Using deep learning techniques, in particular UNet networks and Sentinel-2 images, the primary objective of this research is to detect urban change. Knopp et al. (2020) showed that deep learning can be used to successfully segregate burned areas using data from Sentinel-2. While there are a number of ways for segmenting areas using satellite pictures, the most of them need extensive preprocessing in order to be effective. They integrated several sensors and algorithms into a fully autonomous processing chain powered by deep learning. Their method makes advantage of the U-Net network. The use of spectral bands, neighbouring IR domains, and IR wavelengths was used [4].

Ahangarha et al. [5] presented an unsupervised method for detecting changes using machine learning. They compared their method to PCA and IR-MAD, two methods that have been utilized before. The machine learning approach has far higher accuracy and much better performance. Wan et al. (2018) developed a technique for detecting shifts using data from many sensors in remote sensing images. There is now a histogram that can be sorted. Adjusting the contrast in multi-sensor images is greatly aided by their technology. However, the generated map has several false positives and blind spots [6]. Cao et al. (2017) created a unique deep-network-based difference-image (DI) synthesis method for change recognition in multitemporal remote-sensing photographs. They used a deep learning model and an unsupervised approach to learn neighbourhood-level and pixel-level features. Both quantitative and qualitative assessments showed improved performance compared to earlier techniques based on textures and pixels. Their method successfully illustrates the superior performance of deep learning networks [7]. This study presents a supervised deep learning (DL) based activity detection technique to generate an accurate change map, which is crucial given the necessity of improving the quality of binary CD maps in remote sensing photographs. DL's outstanding performance and potential in the realms of pattern recognition and nonlinear issue modelling has led to its increasing popularity for handling CD issues using multitemporal remote sensing imageries. The purpose of using DL algorithms, and convolutional neural networks in particular, is to monitor the environment and divide it into transformed and unaltered sections.

The proposed method was put to the test using data collected by Onera Satellite Change Detection (OSCD). This study used the Onera Satellite Change Detection (OSCD) dataset [8] to evaluate the proposed CD method. Large, annotated datasets are included in this set, which may be used to train models that can handle higher levels of complexity. Sentinel-2 satellite images were utilized to compile the dataset, which includes locations with varying degrees of urbanization across a wide range of countries. These data sets also include the real world's information. This satellite captures images at resolutions of 10–60 meters in 13 wavelength bands including the UV, IR, and short ranges. Twenty-four cities all across the world contributed to this dataset.

The research presented in this article aims to provide a U-Net activity recognition architecture that could function independently of pretraining and classification strategies. This architecture can be taught from scratch since it employs a patch-based approach. For the purpose of segmenting medical images, Olaf Ronneberger et al. developed the U-Net architecture (Figure 2). In this design, you may go either one of two routes. The background of the picture is retrieved through the primary path, which is the compressor or contraction route. Layered convolution and max-pooling layers make up the encoder. The symmetric growth route, or decoder, is the alternative method that enables pinpoint positioning by transpose convolution [9]. This is a fully connected convolutional network from input to output. To rephrase, it's just a neural network, with no extra layers, thus it can handle images of any resolution. In order to improve upon SegNet, U-Net inserts a skip link into both the encoding and decoding stages. After the first cryptographic segment, these links in an encoder-decoder architecture link layers at the same recording scale. In order to produce accurate predictions of classes with exact boundaries in the output image [10], our study is motivated by the fullness of abstract and local statistical and mathematical methodologies encoded with spatial information accessible in the network's foundational layers.

Many processes go into making a remote sensing picture [2]. At first, electromagnetic energy must be obtained; this might come from the Sun or any transmitter on the satellite carrying the sensor. The energy emitted from the source eventually reaches Earth's surface, where it comes into contact with the atmosphere. light is reflected, absorbed, or transmitted by things on Earth once light reaches the surface. Emission might originate from either the surface of the earth or the observed object. The energy that has been reflected or emitted is sent to a remote sensing platform, which then detects and turns it into a photographic picture or an electrical output, which is then sent to a data recording center, which stores the information. The resulting data product is then utilized as input in a remote sensing application after undergoing preliminary processing. When developing a remote sensing system, it's important to gather additional, contextual ground truth data that may be utilized in conjunction with the sensing data for purposes of analysis and interpretation. The findings may then be used to resource allocation and management. Instruments that detect electromagnetic radiation reflected or emitted from Earth's surface are known as remote sensors. The quality of the datareceived from a sensor is defined by four basic resolutions, which include below features;

Spatial resolution: specifies the sensor's ability to tell the difference between very tiny things on the ground. It is often specified in terms of linear measurement, such as 1 meter, 1 kilometer, etc. The excellent resolution suggests that even tiny things may be distinguished.

Spectral resolution: determines the data collection band's spectral bandwidth. The bandwidth of a spectral band decreases as spectral resolution improves. The spectral resolution of a picture is defined by the number of spectral bands it contains and the width of each band (for example, 4, 8, etc. or red, green, blue, NIR, Mid- IR, thermal, etc.). Certain spectral bands (or combinations thereof) are particularly useful for locating certain characteristics of the ground. To put it simply, a hyperspectral picture has hundreds of bands, whereas a panchromatic image has only one (black and white). Color images have three (red, green, blue).

Radiometric resolution: specifies how well a sensor can tell the difference between two things based on the amount of energy each emits or reflects. It specifies the minimum reflected/emitted energy level detectable by the detector. The higher the resolution, the more subtle changes in the reflected or emitted energy may be detected.

***Temporal resolution**:* It describes how frequently a sensor captures an image of a certain geographic region. It's how long it takes for the satellite to make one revolution around Earth. It is the time span during which a satellite will return to the same location on Earth for a second pass. In certain cases, it may be expressed in hours rather than days.

These four fundamental resolutions characterize the RS pictures. The applications provide the range of allowed values. In the case of cloud-tracking applications, a spatial resolution of around 1 km would suffice, whereas in agricultural applications, a resolution of a few tens of meters would be preferable [15]. Sensor parameters, surface features, atmospheric influences, earth motion, and other factors all contribute to inaccuracy in the obtained pictures. Because of this, image processing is required before the photos can be utilized as input in a program [15].

RESEARCH METHODOLOGY

Change detection for satellite images utilizing image processing and deep learning is shown in detail in figure 1 above. Images of several types have been gathered from sensors and preprocessed as part of the data collecting process. There should be inconsistencies in the data since sensors might give forth erroneous readings. Those items must be removed, or else the whole picture dataset must be filtered using one of many filtering methods. Both input pictures (i1,i2) have had their spectral and textural information removed. We pull in a wide range of characteristics, including binary features, spectral features, histogram-based features, the Saliency Map Calculation, and more. This statistic is used in both the training and testing phases of financial feature generation. Both real-time and simulated data sets have been utilized for model training and testing using the convolution neural network (CNN).

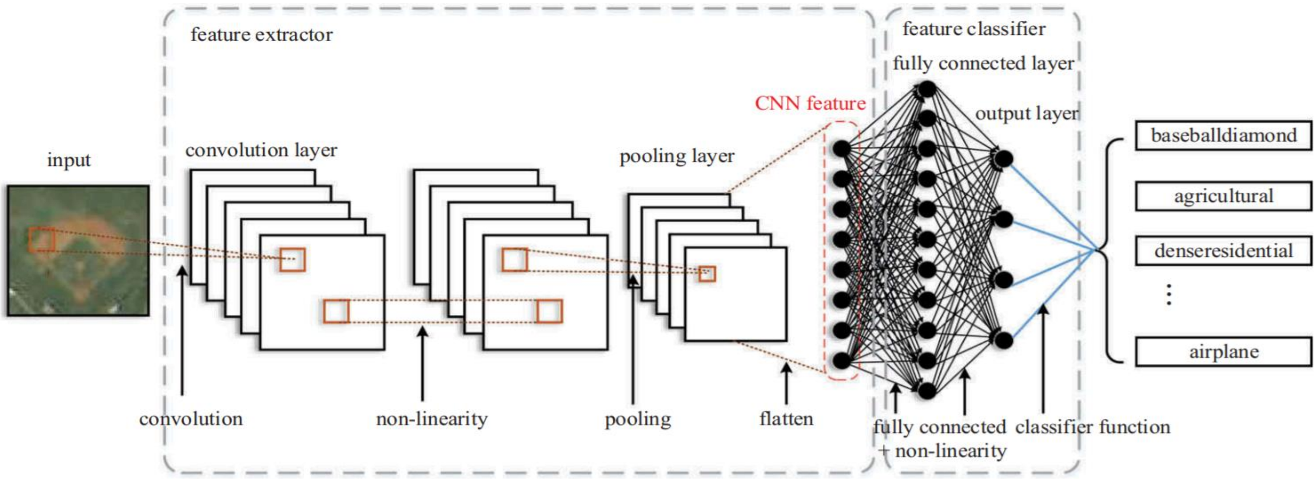

Figure 1: CNN framework applied for change dtection

Humans perceive the texture of any item using three categories of pattern characteristics: spectral, textural, and contextual cues. These are the primary things to consider when interpreting color images [16]. Spectral characteristics are variations in average values for various bands or sections of the electromagnetic spectrum [16]. The spatial changes of these tones in a band are referred to as textural characteristics. Contextual characteristics are information collected from graphical data blocks around the region of interest [16]. Tone refers to the fluctuation of gray levels in a picture, whereas texture refers to the spatial distribution of these gray tones. Tone and texture are inextricably linked. Tone and texture, in addition to context, are constantly present in every photograph. However, any of them may become dominant at any moment. If a tiny part of an image has minimal variation in gray tone characteristics, tone becomes the dominating feature; if it has a considerable variance in a feature of different tones, texture becomes the dominant feature.

Texture analysis may assist in segmenting an image into parts of the same texture, recognizing or classifying an item, finding edges in an image, object identification, and industrial inspection, among other things. In [16], Haralick et al. described a technique for categorizing visual data by extracting texture information from images on a resolution cell or block basis. Based on the gray level co-occurrence matrix (GLCM), he defined a set of fourteen texture attributes. For a given displacement vector, GLCM creates a histogram of the co-occurrence of pairs of grey-levels. The frequency of occurrence of two pixels with intensities i and j separated by a distance of (x, y) inside a particular neighbourhood is represented by the matrix element P(i, j | x, y). The GLCM matrix has the same number of rows and columns as the image's gray levels.

The propsoed method for detecting shifts Various image processing techniques, including image filtering, image scaling, and picture normalization, were first applied to the problem of misclassified occurrences. Module training for change detection between two objects using CNN-based feature extraction and selection. Extraction of features for successful detection has been completed, and these features include brightness features, chrominance features, histogram-based features, and others. Both the training and testing phases have made use of a deep Convolutional Neural Network (DCNN) based on RESNET. Two visual objects have been compared using a real-time image dataset to find any differences. The components of the proposed system are described and illustrated below.

A convolutional layer serves as the foundation of a CNN. During convolution, a convolutional kernel of a fixed size is used to perform an operation on a small, nearby subset of the data. The convolutional kernel is a learnable weighted sum. An objective function is used to feed data into the convolutional layer, and then a binary feature map is generated. The subsequent convolution layers may take the feature map as their input. In this way, more complicated features may be extracted by layer-by-layer stacking numerous convolutional layers. To further reduce the model's memory footprint, the cells in each feature map contribute the strength of a convolutional kernel in an activation function. This guarantees that the structure's dimensionality does not significantly increase as the number of convolutional layers increases. Therefore, this model may help in the development of a more intricate network architecture.

A combining layer is often employed after a convolutional layer. Some common pooling layers are the deepest, the next-to-deepest, and the randomised ones. The largest and averaged pooling algorithms choose values from neurons with the highest and averaged likelihoods, respectively, whereas the randomised pooling algorithm selects values from neurons depending on the likelihoods of their neighbors. Overlaying pooling and geometric pyramid pooling are two alternative forms of convolution layers that often outperform the more common pooling layers. No of the type used, max pooling aims to gather features while not worrying about their precise placements, allowing the connection to learn crucial information despite a little change in the input layer. Further reducing the computational burden of supervised learning, a wavelet transform keeps the same number of feature maps from the previous layer while simplifying their spatial structure and keeping the most important information in the feature vector. Binary features, Sobel features, autoencoder features, histogram features, and certain GLCM base features [10] are just a few examples of the features that have been retrieved.

One completely connected layer is really composed of several concealed ones. There are several neurons in each buried layer, all of which are connected to the neurotransmitters in the layer above them. One-dimensional (1D) demographic growth produced by flattening retrieved features close observation in the max - pooling serves as the input for a feature map. For classification purposes, a highly integrated layer should map these features onto a binary classification space while staying in phase with the activation function. The classifier performance is typically output by a linear classifier used by the output layer. Max pooling is now the most popular classification technique used in CNNs.

Furthermore, a CNN relies heavily on its activation and loss processes. To better comprehend on a linear discriminant basis, artificial neurons are often nonlinear. Most networks use some variant of the Sigmoid, Batch Normalization (ReLU), or Additional motor functions. Kernel functions, also known as optimization problems or precise solutions, are used to calculate the historical differences between the observed and estimated amounts and the real image. Model over fitting may be prevented by include extra units in the gradient descent, such as L1 regularization and L2 regularization. You may think of the L1 and L2 regularizations as bounds on the values of the loss function.

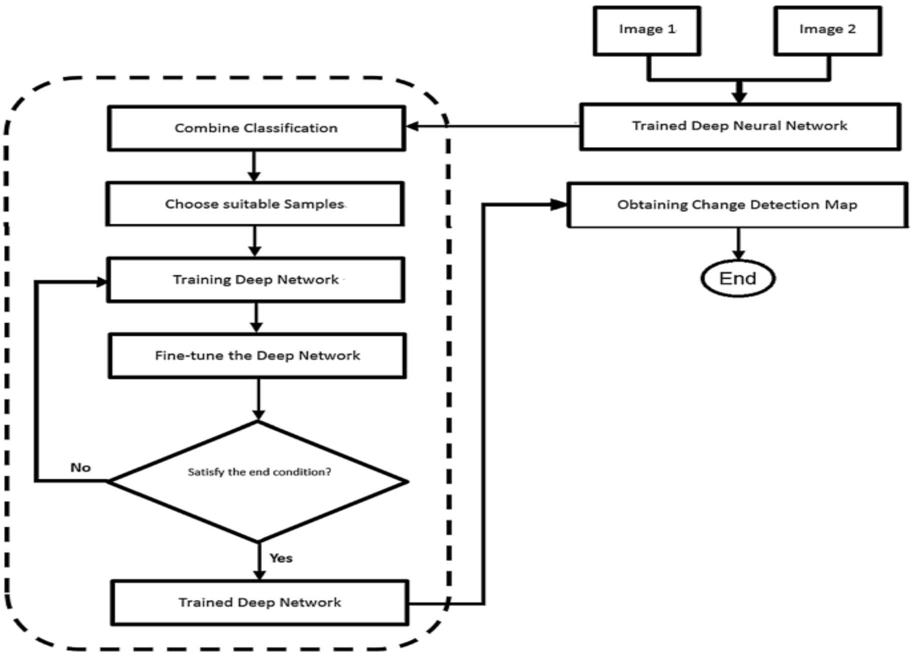

Figure 2. proposed change detection model flowchart architecture

This research proposed an approach of change detection between two SAR images using deep CNN. To achieve this outcome system deals with two different image objects of specific locations [10]. Both images were captured by the same area but in different time zones [5]. The feature has been extracted in the convolutional layer using CNN, while optimization has been done in the pooling layer. The dense later provides the similarity or percentage of change of new image with previous one. The below algorithm demonstrates the step-by-step execution performed using RESNET and imageNet CNN.

RESULTS AND DISCUSSIONS

The accuracy of the change detection algorithms can be measured through qualitative or quantitative parameters. Qualitative analysis of the results involves visually comparing change map with the change on the ground. For quantitative analysis, the error is measured and compared with the ground truth data. Quantitative analysis has been more popular as it is easy to quantize and compare the error. In this thesis, the following parameters have been used to measure and compare the accuracy of various methods

Several different deep learning frameworks that come equipped with their own libraries are used in the experimental investigation. Python is used throughout the whole system, and there are around 1500 lines of code in total, which includes all of the TensorFlow library files. The NVIDIA GFORCE GTX (TITAN) equipped with 12GB GDDR5X and the Intel(R) Xeon ES 1607V 2.3GHz equipped with 16GB DDR3-1866 ECC are used for all of the implementation work. In this particular investigation, a classification model was constructed using nine components of the OSCD dataset, and three of those components served as test data. Table 1 contains the quantitative evaluation of the U-Net architecture that was carried out. In the table, you can see information on accuracy, recall, F1 Score, and kappa. We tested more than 13 bands in order to provide a comparison of the RGB multilayer network. In comparison to all of the data from the Satellite Sentinel Project, the RGB channel has less data; in addition, it has numerous training and learning modules, which means that more great training time is required. As a consequence of this, it is very necessary to use all bands. Figure 3 shows a graphic representation of the Unet network's results.

Table 1: Performance analysis of proposed model using various DL approach

DL Framework	Accuracy	Precision	Recall	F-score
RNN-LSTM	85.40	84.40	85.70	86.50
R-CNN	92.40	93.90	94.20	94.70
F-CNN	93.55	92.60	93.10	93.05
HCNN	94.90	91.50	91.80	92.10
DNN	94.20	94.30	94.15	93.70

PNN	95.30	95.70	95.80	95.60
DCNN (Proposed)	**96.10**	**95.30**	**96.40**	**96.50**

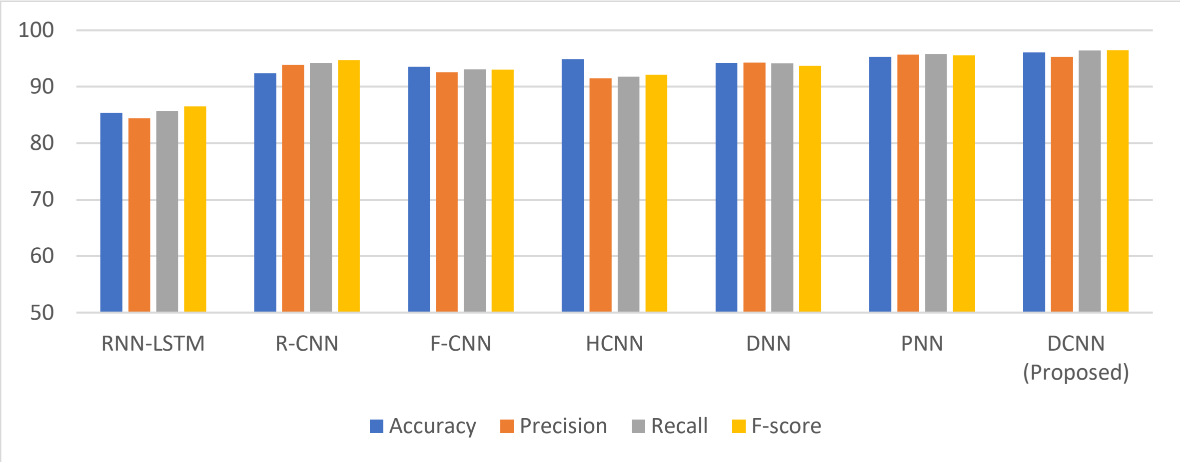

Figure 3 : overall analysis of proposed model with various deep learning frameworks

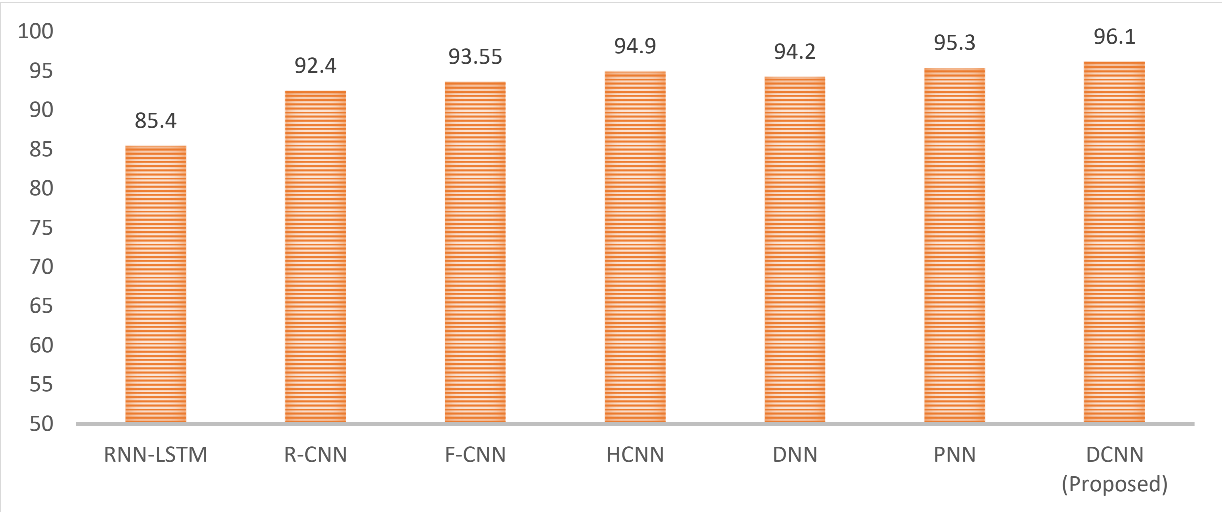

Figure 4 : Accuracy analysis of proposed model with various deep learning frameworks

Above, Figure 4 demonstrates an evaluation of the proposed model in terms of accuracy with various deep learning frameworks. As a result, we conclude the proposed deep CNN module obtains higher accuracy over all state-of-art deep learning classification algorithms.

CONCLUSION

In this study, we provide a deep learning framework designed specifically for change detection. The speed of the network is a step toward more efficient operation of land data available through projects like Copernicus and Landsat, in comparison to other non-performance-degrading approaches of recognizing changes. Machine learning can organize remote sensing images into a hierarchy, allowing it to pick out distinct features. This goes beyond just counting significant differences between images since it involves semantic labeling of changes. This is accomplished via the usage of skip connections. Networks should be able to tell the difference between faked and actual changes, as the former are labeled as database updates, bringing the overall accuracy up to roughly 95%. In the future, we want to combine this data with radar photos and explore further applications for it. Customers do not have direct access to the servers used by cloud storage providers. Instead of building individual servers for each customer, cloud storage providers adopt a model in which the resources needed by several customers are pooled together. If users provide data that might be dangerous or otherwise strange, your servers could be at risk.

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