An Overview of Deep Learning Networks for Remote Sensing Applications

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Abstract—To study and understand the world around us, remote sensing specialists rely on aerial and satellite photographs. Today, deep learning models necessitating extensive data or specialised data are employed in many remote sensing applications. Sometimes, the spatial and spectral resolution of Observation satellites of the planet earth will fall short of requirements due to technological constraints in optics and sensors, as well as the expensive expense of upgrading sensors and equipment. Insufficient information might reduce a model's efficiency. The efficiency of deep learning frameworks that rely on data can be improved by the use of a adversarial networks, which is a type of technique that can generate synthetic data. This is one of the best innovative developments in Deep Learning in past decade. GANs have seen rapid adoption and widespread success in the Remote Sensing sector. GANs can also perform picture-to-image translation, such as clearing cloud cover from a satellite image.This paper aims to investigate the applications of different Adversarial Networks in the remote sensing area and the databases used for training of GANs and metrics of evaluation.

Keywords- Remote Sensing, Clouds Removal, Deep learning, Geneartive Networks.

I. INTRODUCTION

As deep learning has developed rapidly in recent years, it has become a popular method for analyzing remote sensing data [1]. Large models made up of artificial neural networks with multiple layers are used in deep learning techniques to computer vision.

For applications like recognizing objects and picture categorization, these networks may learn to contextualize what they see. Land cover categorization, semantic segmentation, object detection, and change detection are just some examples of the kinds of geospatial analysis tasks that may be performed with the use of deep neural networks with remotely sensed data [2].

Deep learning methods like recurrent networks, convolutional networks have traditionally been used to do these sorts of jobs. Although the aforementioned techniques have shown promise, recent developments in deep learning models for computer vision problems have begun to exceed them.

The transition to using deep learning with remotely sensed imagery is a natural one, as the vast bulk of remote sensing data is imagery, which CNNs excel at. However, many deep learning algorithms face the problem of needing thousands or even millions of photos to train a model. It is challenging to collect big enough datasets in remote sensing for training these models since data acquisition might be costly or time-consuming. Data augmentation and other techniques have been developed to help provide more data for use in remote sensing applications.

Synthetic data can be generated by the deep learning model generative adversarial network (GAN) [3]. GANs may learn the underlying data distribution from a given set of example images, allowing them to generate new images with the same features as those in the training set.

In section II, various types of GAN variants are discussed, section III gives the applications of Adversarial Networks in remote sensing. Section IV deals with evaluation metrics and the last section gives the conclusion.

II. TYPES OF DEEP LEARNING TECHNIQUES

A. Convolutional Networks

One of the popularly used deep models, CNN was developed to handle information presented in a number of arrays [4]. This makes it a good option for processing.

The information from many bands of remote sensing imagery with the same pixel layout regularly. CNN is made up primarily

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of three Layers of Convolution, Layers of Pooling, and layers which are interconnected.

Visual abstraction is essential for the process of interpreting remotely sensed images. CNN, a standard deep learning representation, handles visual abstraction. CNN is a major technological advance. CNN not only deals with the interpretation of remotely sensed images, but also with the classification of scenes based on those images, the retrieval of images, and the detection of objects based on those scenes.

Many popular architectures are ALEXNet, VG Net, ResNet [5] and Inception-v4 [6].

B. Recurrent Neural Networks

In several applications, including signal processing, [7], [8], recurrent neural networks stand out as a superior learning technique. By explicitly reusing the neuron's output from the previous unit of time along with the subsequent input, RNNs manage temporal data dependencies in a clearer fashion than convolutional neural networks.

C. Generative Adversarial Networks

It comprises of two main blocks – The Generative block and Discriminative block. The Discriminator block will attempt to tell the difference between a real image and one that was generated by the Generator block, while the Generator block will attempt to deceive the Discriminator block into thinking that a false image was taken.

MARTA GANs, which are multi-layer adversarial generating networks, are used for acquiring a representation from unlabeled input [9]. The generative block and the discriminative block are main parts of a MARTA GAN. Specifically, discriminator as a feature extractor. To combine the intermediate and global features in order to accommodate the data's complicated qualities fusion layer are used. Since Generator can generate many examples that are liker to the training images, Discriminator can improve by using Generator's data.

This strategy results in two popular remote sensing picture datasets demonstrate a notable improvement in classification accuracy.

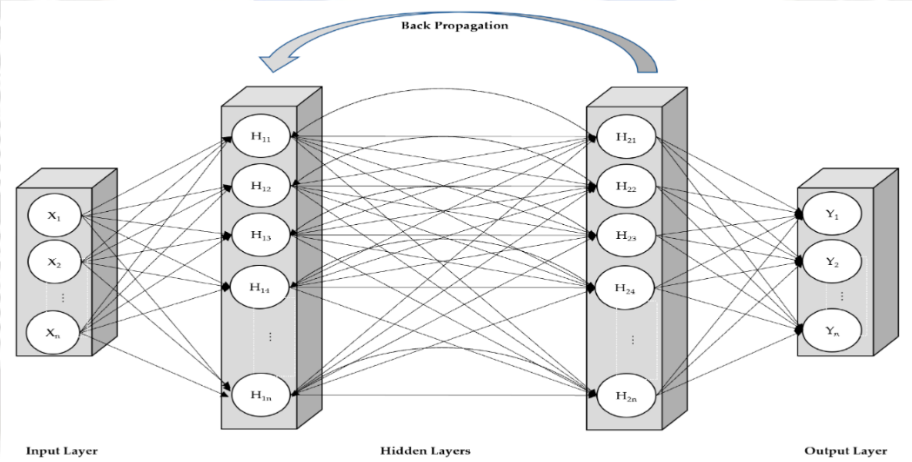

Figure 1: Network Architecture of RNN [8]

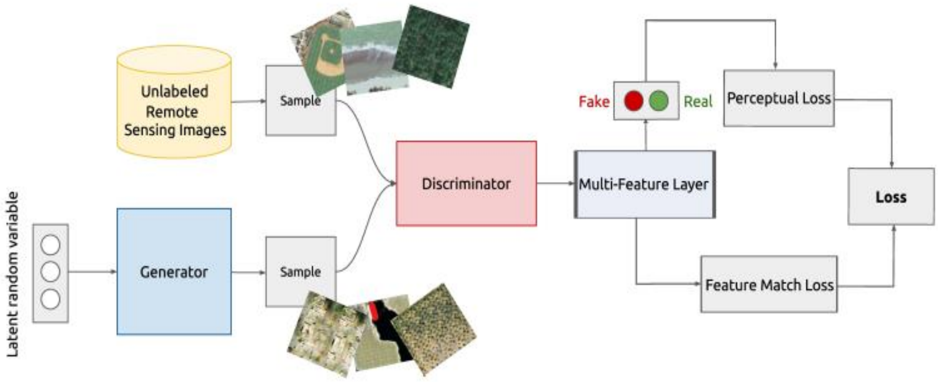

Figure 2: MARTA GAN Architecture [9]

III. APPLICATIONS IN REMOTE SENSING

There are many examples of GANs being used in Remote Sensing. In this section we take a look at how GANs have been put to use in remote sensing.

A. Data generation

For enhancing information, multiple-layer GANs are introduced by Lin et al. [9]. Even with difficult distant sensing datasets, MARTA GANs can learn interpretable representations because it is entirely unsupervised.

To some extent, the issue of distortion was addressed by Han et al.'s [10] proposal of a high-resolution scene or image data generating approach employs Wasserstein GAN technique.

B. Cloud Removal

Clouds frequently obscure the target region in remotely sensed satellite pictures. It is possible to get rid of clouds by retrieving numerous satellite photos of the same area and then manually swapping out the cloudy pixels. Cloud-GAN [11] uses a cycle consistent to learn a mapping from cloudy to cloud-free imagery, allowing it to remove thin clouds from satellite imagery. It is possible to classify cloud cover obstruction as either thin cloud cover, which obscures information only partially, or thick cloud cover, which obscures objects entirely.

C. Object Detection

It has been stated that GANs improve object detection tasks because of their ability to aid in data augmentation, hence increasing the model's robustness. Zhu et al. [12] introduced a multi-branch convolutional GAN, which they abbreviated as MCGAN, in order to generate a variety of diverse samples for use in object detection applications. MCGAN employed one classification branch to forecast the classes of input items and three false data detection branches to increase the variety of generated images. The authors also employed a dynamic samples-selection technique to exclude any artificial data that would have resulted from using a sample distribution that did not match the actual data.

D. Land Cover Classification

To further enhance the generalizability of scene classifiers, GAN-based augmentation can also be applied to remote sensing imagery or scene categorization tasks. The authors in [13] did research in which two scene land-cover classifiers were utilized instead of a single discriminator. As the authors pointed out, using a dual-classifier option will be helpful to eliminate uncertainty close to land cover decision boundaries, leading to more precise results when applied to target photos.

IV. EVALUATION METRICS

In addition to GANs' inherent instability during training, it's also hard to objectively gauge the quality of generated images. The most popular metrics for evaluating GANs in the context of remote sensing are given below.

A. Spectral angle mapper

Automatically matching an image's spectrum to one that has already been determined either in a laboratory or at the outdoors employing a spectrometer or to an endmember is the goal of the Spectral Angle Mapper Classification (SAM).

B. Erreur relative globale adimensionnelle de synth`ese

The spectral quality property of the newer images improves as the ERGAS index drops. ERGAS is a popular metric of evaluation particularly used in remote sensing applications.

C. Frechet Inception Distance

The FID measures the level of dissimilarity between feature vectors derived from actual and synthetic pictures. The FID score takes input features and embeds them into a specific layer of the Inception Net model.

V. DATASETS

A. EuroSAT Dataset

This research makes use of 27,000 labelled photos from across 10 categories taken from the EuroSAT assessment datasets [14]. There are 2,000–3,000 photos in each category. Classes include things like trees, medicinal plants, roads, factories, grasslands, plants, cities, and lakes.

B. xBD Dataset

It's the most extensive collection of remote sensing data for assessing damage to buildings [15]. It assesses the damage done to buildings, which divides them into four categories: undamaged, damaged, severely damaged, and destroyed. The xBD data collection depends on Maxar/DigitalGlobe open data program. 22,068 remote sensing photos representing 19 different types of disaster occurrences and 850,736 buildings make up the entirety of the xBD data set.

C. NWPU-RESISC45 Dataset

There are 31,500 satellite photos for remote sensing in the NWPU-RESISC45 collection [16], and they've been divided up into 45 different scene types. There are about 700 photos in each group.

VI. CONCLUSION

There have been significant advancements in the quality of remote sensing photographs over the course of several decades. It is staggering how many articles have been written on the topic of scene categorization in remote sensing images, with a focus on deep learning-based approaches. One of the recent approaches used is GAN. This paper focused on the applications of GAN in the are of remote sensing such as object recognition, land cover usage, pan sharpening etc. This paper gives a brief overview on the variants of GANs used in remote sensing and their evaluation metrics used.

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