IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

DEEP LEARNING For REMOTE SENSING APPLICATION: A REVIEW

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Abstract: The findings of remote sensing data in the art need to be analyzed and interpreted so that it can provide a worthy study that is more transparent and useful for scientists in different disciplines. In recent years, deep learning techniques have overcome the essential task of dissolving many remote sensing data image processing applications. This work observes an analysis of compatible and appropriate deep learning (DL) applications which is compatible with remote sensing (RS) data covered by a number of scientists to evaluate the state of different DL algorithms. This search therefore involves applying research to DL algorithm forms and their application in various fields of satellite image processing, such as Neural Network (NN), Convolution neural network (CNN) which summarized more RS data information. Finally, a short-lived conclusion on DL strategies that will facilitate a variety of types of hypothetical authoritative frame work for DL modulation in various remote sensing applications.

Index Terms - Remote sensing, Image analysis, Deep learning, Neural networks, convolutional neural networks.

I. INTRODUCTION

In this report, a widespread analysis of deep-learning techniques to enhance remote-sensing observations based on precarious tasks, including single and multi-band super-resolution, demise, reconfiguration, pan-sharpening, and fusion, among others. In addition to the systematic analysis and comparison of the previously approved structures, different research directions may also be discussed [1].

Consequently, in latest years, there are already considerable constraints in understanding how to incorporate deep learning (DL) algorithms for remote sensing (RS) data in various remote sensing processing applications, such as semantic segmentation, image fusion, object detection and land use land cover classification[2]. The remote-sensing organization, on the other hand, has changed its approach to DL since 2014, and DL algorithms have received tremendous achievements in many image interpretation functions such as semi- segmentation and recognition for all land cover objects. In addition to, absolutely convolutional neural networks (CNN) are used to learn the implicit characteristics of the data automatically in order to categorize the concepts [3].
Until now, most DL review studies have either been general reviews of the DL algorithm's progress or specific topical reviews of a few hot fields.

Since a few tests were included in a survey of big data analytics in satellite data, numerous important field areas have not even been studied. It focuses on the use of DL for the fusion of remote sensing data in terms of context and has omitted its use in other primary aspects of remote sensing applications. In all other terms, a proper and accurate analysis concerning on use of neural network has not been conducted so far in the field of remote sensing [4]. A holistic questionnaire was done than others, but highlighted some extremely rare sub-areas for remote sensing while missing many other deserving sub-areas, including such applications for image classification. In many other different community within the field of remote sensing and the quantity of recent articles, DL algorithms were also used. For instance, the numerous types for which DL has been used before the factors involved DL and remote sensing investigators are particularly effective within these surveys[5].

II. PERCEPTRON NEURAL NETWORK TO DEEP LEARNING

DL is an algorithm of learning based on Neural Networks Neurons or units with a certain activation and parameters ={W,} In reality, they were representative of a neural network[6] [7]. Thus, learning techniques consist of several other materials that encode X€RD raw data and map it to a latent representation h€R M on a nonlinear mapping, as shown in Eq.1 in the following :

$$h = f\ (Wx + ß) \qquad (1)$$

ß is a bias vector where W is a kernel function to be measured throughout processing, and f refers for a non linear model, such as the non - linear activation logistic function or a hyperbolic tangent to represent the encoded function h, which is then used to reconstruct the x input by backward encoding, culminating in the reconstructed y input as illustrated in Eq.2.

$$Y=f\ (W^{\wedge}\ 'h+\beta')\ (W^{\wedge}\ 'h+\beta) \qquad (2)$$

Where W 'is initially limited to the mode of W' = W [8]. In general, a neural network (NN) is described as a "deep" neural network with many hidden layers, but the term "deep learning" is called a "deep" neural network. This became a significant topic of controversy in the initial periods, as seen in Fig.1. 1990s [9], but it was widely overlooked by the machine-learning community at that time schooling concentrated on training algorithm. In contrast, machine learning and remote sensing technologies have not yet received substantial attention in this critical duration of time[10] .

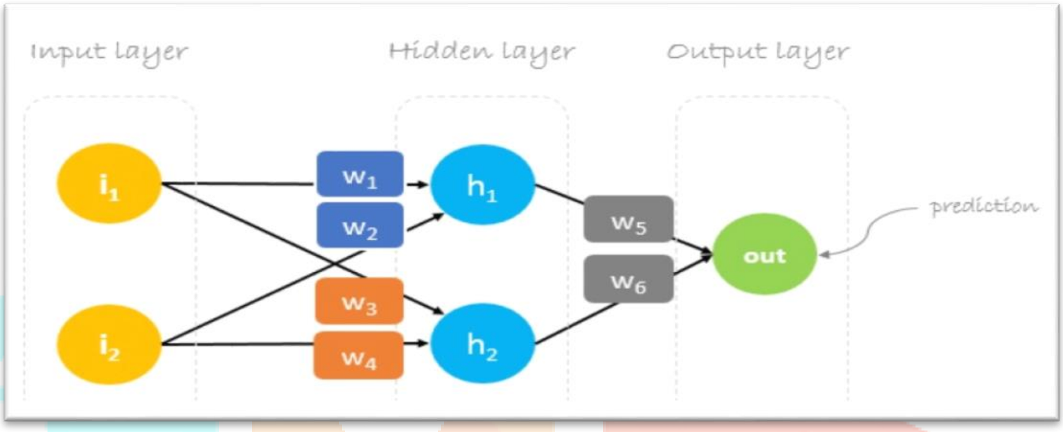

figure.1:neural net work design

Deep Neural Networks (DNNs) focused upon About 2006, deep feedforward networks and DL became theoretically possible to some college education levels with the advantage of unsupervised learning.The convolutions neural network (CNNs) used for remote sensing image classification is another model which describes the major effort in DL [11]. CNN framework thus proposes two main steps of training input data via network, then extraction and classification attributes. For the first step, there are two parts: forward and backward part as clarified in Fig.2. The input images are fed through the network in the forward part to obtain an abstract representation that are being used to determine the loss cost with regard to the ground truth labels given. Based on the loss cost, the backward part computes the gradients of each parameter of the network. Then all the parameters are updated in response to the gradients in preparation for the next forward computation cycle. After sufficient iterations of training, in the second stage, the trained network can be used to extract deep features and classify unknown image[12].

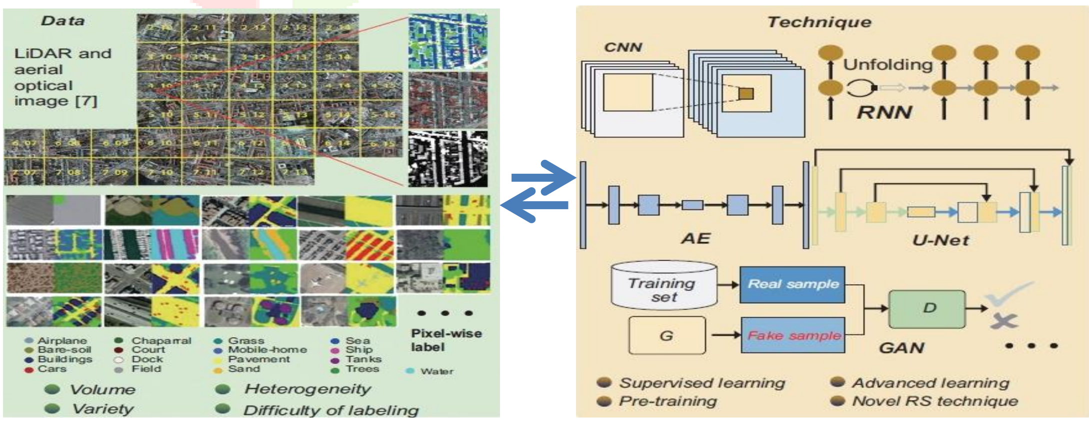

figure.2: learning methods for remote sensing images interpretation[13]

III. DEEP LEARNING APPLICATION FOR REMOTE SENSING DATA

The integration of DL in remote sensing applications offers superior data including quantitative statistical analysis and visual interpretation[14]. Thus, in remote sensing studies such as LULC classification, semantic segmentation and object detection, CNN is the most universal method. In contrast, DL recently optimized that, as shown in Fig.3, it can be introduced for most image processing applications related to remote sensing data processing [6].

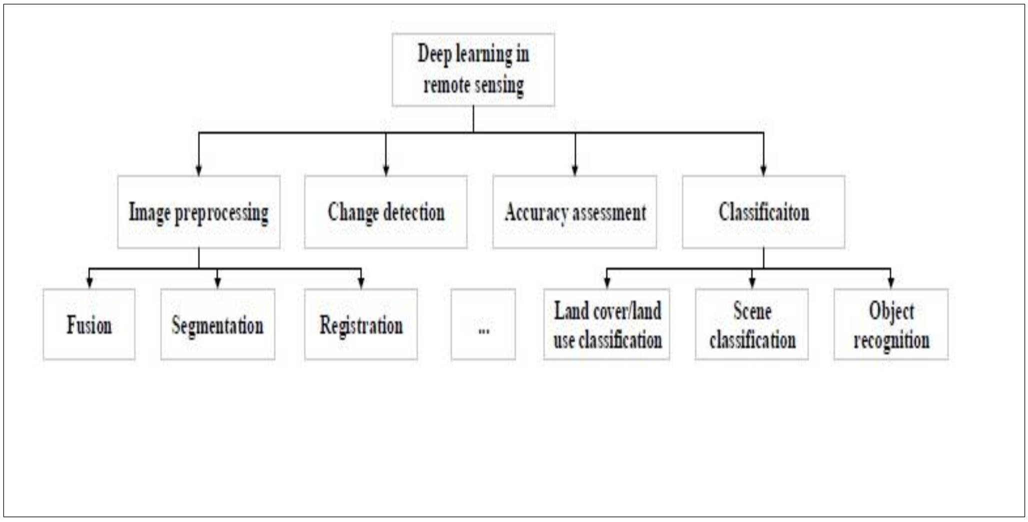

Figure.1: DL processing steps for remote sensing data

3.1Image fusion

For remote sensing images for low resolution compared to multi spectral images and high resolution panchromatic images[15], the fusion technique obtains a significant approach. In other terms, a familiar application of remote sensing data to obtain high spectral and spatial image resolution is the pan sharping image fusion technique [16].

3.2 Image registration

For remote sensing images for low resolution compared to multi spectral images and high resolution panchromatic images, the fusion technique obtains a significant approach[11]. In other terms, a familiar application of remote sensing data to obtain high spectral and spatial image resolution is the pan sharping image fusion technique [17]

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3.3 Object detection

Another important objective of the object detection technique In a single image scene, It is possible to observe different artifacts such as airplanes and urban villages and training samples accumulated in a fixed-size window [18].

3.4 Land use land cover classification(LULC)

Early DL-based LULC classification scholars focused mostly on feature representation or learning, while other simpler classification algorithms were used in the final classification [19]. This was principally because extracted networks present excellent spatial representation and capacity via maintaining good spatial knowledge that is mostly generated by hierarchies rather than generating low-level features. For particular, by using aggressive level wiser unmonitored pre-training [20] Proposed unsupervised extraction for deep features to be classified. Apart from that [21] mentioned how to learn and enhance the quality of features to recognize hyperspectral remote imagery, a multi-scale CNN algorithm was published. In comparison to the DL model used in the land cover classification, CNN has also earned the greatest reputation [22]. There were also numerous studies in which distinctive adaptations were proposed to the DL solution(s) to classify features of the more descriptive land use pattern. For illustration, a CNN With rotation equality was mentioned by [12] and assigned to two semantic-labelling parameters of such sub-decimetre land cover.

IV. Conclusion

Remote-sensing researchers have been using the big data techniques to solve these complicated issues and have developed a long wave of aggressive studies. In this research, we review such innovations, In this research, DL-related publications were analyzed in detail through a meta analysis in nearly all sub-areas of the remote sensing domain. Subsequently, some main subfields include the enhancement of contrast images, classification of patterns, machine vision[23], and use of DL in remote sensing applications. Finally, a more in-depth analysis was carried out to identify and address. In all of these subfields the use of DL algorithms which differentiates our analysis from previous neural learning recent studies and remote sensing reviews.
[24]Several key subfields using deep learning methods in remote sensing processing , including feature selection, image calibration, scene classification, and object detection, were subsequently summarized. Finally, in order to explain and analyze the use of various deep learning and neural networks algorithms in all of these subfields, a deeper analysis was performed, which distinguishes our research from previous deep learning and remote sensing studies.

Conflict of interest

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.and there is no financial support for the research, authorship, and/or publication of this article.

Acknowledgment

The author appreciates the assistance of the instructors in the remote sensing center of Mosul University, who are experts in this field for their helpful suggestions and cooperation to guide this article forwards the best.

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