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Remote Sensingusing Deep Learning: A Review

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Abstract: Deep learning is the state-of-the-art of machine learning. Remote sensing is acquiring information without physical contact. A lot of image processing techniques have been developed to support the understanding of remote sensing images and to pull out as much as possible information from the images. This literature review demonstrates that deep learning attains the outstanding performance in classification of remote sensing images.

Introduction

Machine learning is becoming essential to understanding what is happening and what will happen and same apply to earth using remote sensing data. Deep learning is widely used in big data analysis and has been at a place of one of the 10 advance technologies of 2013[23]. It is evolved by neural networks (NNs) concerning more than two layers . As their shallow complement, deep neural networks make the most of feature representations learned exclusively from data, instead of domain specific knowledge. Latest research in this area have proved deep learning a very successful tool, sometimes even intelligent to surpass human ability to solve extremely computational tasks (see, for instance, the highly mediatized Go match between Google's AlphaGo AI and the World Go Champion Lee Sedol [23]. After Motivation from advances, deep learning became a model in many areas. The most important dissimilarity between deep learning and conventional machine learning is its performance when size of data increases. On small data, deep learning techniques don't do that well as deep learning algorithms require a greatquantity of data to recognize it exactly. Deep learning heavily depends on high-end machines and includes GPUs (Graphics Processing Units). Deep learning enable system think like human brains using artificial neural networks and Figure 1 shows the performance graph of Deep learning over older learning techniques.

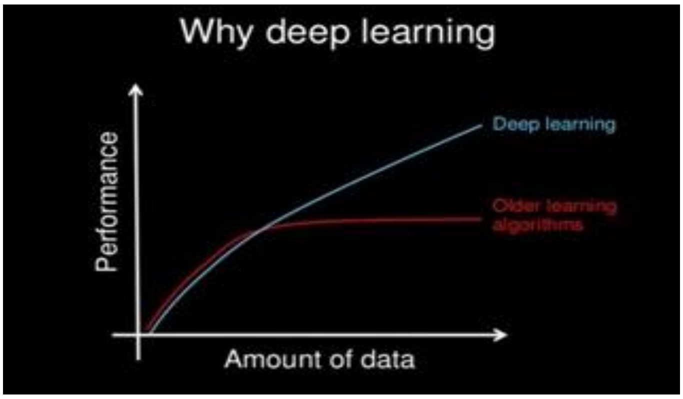

Fig. 1. Deep learning Vs older learning techniques

Deep Learning Techniques:

Following are the techniques that allow deep learning to solve a variety of problems.

1. Fully Connected Neural Networks

Fully Connected Feed forward Neural Networks are the standard network architecture used in most basic neural network applications. Fully connected; means that each neuron in the preceding layer is connected to every neuron in the subsequent layer. And feed forward means that neurons in any preceding layer are only ever connected to the neurons in a subsequent layer. Each neuron in a neural network contains an activation function that changes the output of a neuron given its input.

2. Convolutional Neural Networks

Convolutional Neural Networks (CNN) is a type of deep neural network architecture designed for specific tasks like image classification. A CNN is composed of an input layer. However, for basic image processing, this input is typically a two- dimensional array of neurons which correspond to the pixels of an image. It also contains an

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output layer which is typically a one- dimensional set of output neurons. CNN uses a combination of sparsely connected convolution layers, which perform image processing on their inputs. In addition, they contain down sampling layers called pooling layers to supplementary reduce the number of neurons necessary in subsequent layers of the network. And finally, CNNs typically contain one or more fully connected layers to connect our pooling layer to our output layer.

3. Recurrent Neural Network

The recurrent neural network (RNN), unlike feed-forward neural networks, can operate effectively on sequences of data with variable input length. This means that RNNs uses knowledge of its previous state as an input for its current prediction, and we can repeat this process for an arbitrary number of steps allowing the network to circulate information by means of its hidden state through time. This is similar toproviding a neural network a short-term memory. This feature makes RNNs very effective for working with sequences of data that occur over time, For example, the time-series data, like changes in stock prices, a sequence of characters, like a stream of characters being typed into a mobile phone. RNNs work well for applications that involve a sequence of data those changes over time. These applications include natural language processing, speech recognition, language translation, image captioning, conversation modeling, and visual Q&A.

Remote Sensing

Remote sensing is the procedure of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at different location from the embattled area. Remote sensing data is very significant to monitor the earth as an entire system. Because of the atmosphere conditions our eyes only see the specific portion of the Electromagnetic (EM) spectrum. Our eyes are able toobserve the visible portion – red, green and blue. Healthy vegetation (or chlorophyll) reflects supplementary green light as compared to supplementary wavelengths. It absorbs red and blue light more. With the intention , our eyes observe it as green. But extraordinary sensors are made to see the EM spectrum – unseen to the human eye. For example, vegetation also reflects even more near-infrared (NIR). NIR is invisible to the human eye, but sensors are able to pick up this spectral band. Remote sensors might be passive or active. Passive sensors react to external stimuli. They take natural energy that is reflected or emitted from the Earth's surface. Passive sensors take reflected sunlight as source of energy.Fig. 2 shows LIDAR (Light Detection and Ranging) image in which data collected by NOAA's National Geodetic Survey and Fig. 3 shows Aerial imagery of flooding in Louisiana with remote sensing.

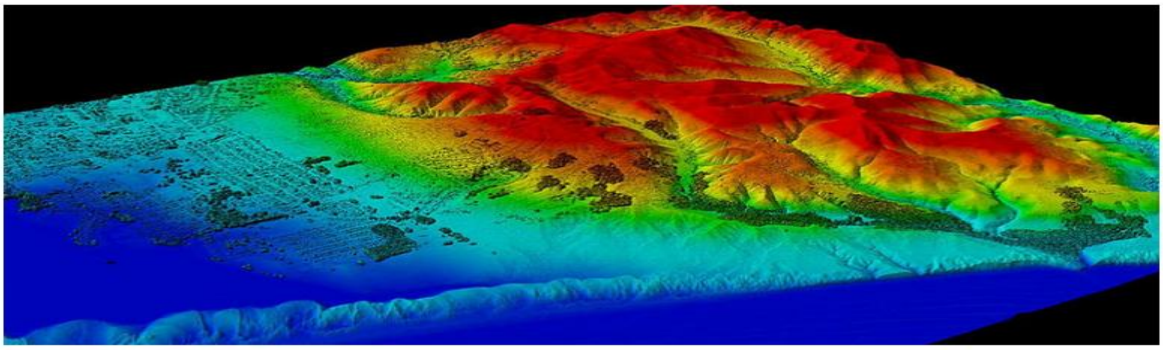

Fig2: Light Detection and Ranging, image formed with data collected by NOAA's National Geodetic Survey.

Fig3:Aerial imagery of flooding in Louisiana. Image formed by NOAA aviators on behalf of the National Geodetic Survey

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Deep Learning Frameworks for Remote Sensing

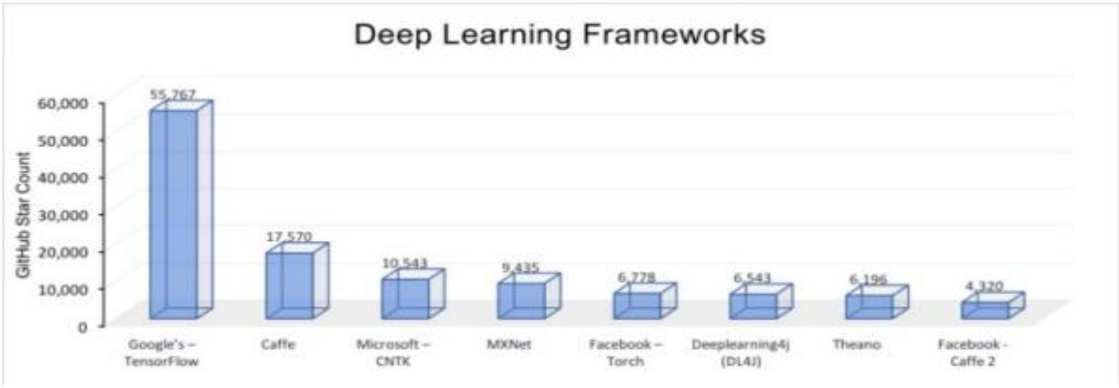

Fig. 4 Deep learning frameworks

Fig. 4.[24] shows open-source deep learning frameworks used for remote sensing.Following steps are performed on image using deep learning:

1. Image Preprocessing:

Prior to data analysis, initial processing on the raw data is performed. Some correction procedures may be applied before the data is given to the end-user. These procedures include radiometric correction and geometric correction .

2. Image Classification

Dissimilar types in an image be able to be discriminated bysome image classificationalgorithms using spectral features which are known as brightness in each pixel. The classification process can be supervised or unsupervised.In supervised classification, the spectral features are extracted from the image. In unsupervised classification, depending on their spectral features the computer program involuntarily groups the pixels of the image into different clusters.

3. Spatial Feature Extraction

In high spatial resolution imagery, Pixel-based methods of image analysis will not work successfully.To completely exploit the spatial information enclosed in the imagery, analysis algorithms using the textural, contextual and geometrical properties are needed.

LITERATURE REVIEW:

Lorenzo Bruzzone *et* al. [1]Proposed data fusion approach for the classification of multisource remote-sensing images . Bayes rule method was used to find minimum error for the classification of pairs of multisource images acquired at two different dates.

Xiaofang Liu *et* al. [2]Proposed weighted Fuzzy C-Means (WFCM) clustering algorithm to perform the fuzzy classification or the hard classification of remote sensing images.

Jie Yu, Zhongshan Zhang *et* al[3] Proposed a new method using the feature texture knowledge with Back Propagation neural network trained by particle swarm optimization. Proposed algorithm improved the classification accuracy and classification speed.

Futian Yao et al [4] Proposed Gaussian processtechnique to classify band selection. Bayesian kernel is appropriate for nonlinear data classification .Using posterior probabilities it is capable to reduce uncertainty. Classification of Hyperspectral remote sensing of images was done effectively in terms of classification accuracy .

Fu Wei et al [6]Proposed spatial and temporal contextual classification based on Markov Random Field (MRF). Poyang Lake. Research demonstrated that spatial and temporal neighborhood related information from different images were able to be used to remove the uncertainty of different types. This process improvedoverall classification accuracy .

Aiying Zhang et al [7]Proposed a new method based on fusionof pixel-based classifier and object-based classifier toperform land classification. The Boosting classifier was chosen as pixel classifier. SVM was taken for object based classifier. Firstly, image was classified using Boosting classifier to acquire the labels of each pixel. Secondly, the image was segmented, and then casting of vote for each block. Highest votes were taken as the label of the block. At last,fusion of the results of vote and the classification results of SVM was performed. Experimental results showed that the considerableenhancement in term of classification accuracy.

Xianchuan YU et al [8]: Focused on two things that "same spectrum with different objects" and "same object with different spectra" .The overall accuracy and kappa coefficient also confirmed its greater performance.

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Jun Wang et al [9]Proposed a novel deep hierarchical segmentation approachfor highresolution remote sensing image. Image segmentation was done with a deephierarchical feature illustration framework.An effective procedure was developedfor multi-scale image representation to address theissue of information uncertainty . Results were obtained on two optical highresolution remote sensing image datasets which confirmed the effectiveness androbustness of the proposed work.
Adriana Romero et al [10]Proposed a greedy layer-wise unsupervised pretraining coupled with unsupervised learning of sparse features. The algorithm was based on sparse representations. The proposed algorithm clearly outperformed principal component analysis (PCA) and its kernel counterpart (kPCA). Results showed that single-layer convolutional networks be capable to extract powerful discriminative features only when the receptive field accounts for neighboring pixels .
Yancong Wei et al [11] In this paper, a deep learning model: Convolutional neural network (CNN) was used for image classification and restoration,
Nicolas Audebert et al [12]This paper investigated the impact of segmentation in preprocessing step for classification of remote sensing images.Segmentation of the image was done and further used by pre-trained deep neural networks as feature extractors for SVM. The paperconcluded that super-pixel algorithms provided better classification accuracy.
Mengyun Shi et al [13]Designed deep Convolutional Neural Networks (CNNs) having four convolutional layers and two fully-connected layers, used to dig out the deep features of cloud. Simple linear iterative cluster (SLIC) method was used to cluster into sub-region. The cloud region was obtained according to the gradient of the cloud map. Experimental results showed that the proposed method was more robust and effective than supplementarycompared methods.
Kaiqiang Chen et al [14]Designed a deep deconvolution neural network with 27Convolution layers to work atat pixel level. As such a deep networkwas error prone and has over-fitting. Therefore, a data augment method atpixel level prediction of tasks was given.
Xiao Xiang Zhu et al [15]Paper analyzed deep learning for remote sensing data,this paper advocated that remote sensing scientists must have expertise into deep learning.
Yancong Wei et al [16]Proposed a deep convolutional network to improve the fusion accuracyusing residual learning with specific adaption of image fusion task. both spatial and spectral domains werepreciselyconserved.
Clayton Connors et al[17]Work explored a semi-supervised deep generative model and autoencoder was constructed that infers class labels without incurring high cost.

Monidipa Das et al [18]The problem of missing data in remote sensing during multitemporal analysis was performed , in this case data at periodic timestamps are missing. This work proposed a deep-learning-based framework (Deep-STEP_FE) for handlingthe missing data in remote sensing time series. The framework has used an ensemble of multiple forecasting modules.

Okan Bilge Qzdemir et al [19]applied stacked autoencoders in remote sensing domain for hyperspectral classification. High dimensional data is most suitable for deep learning. By using autoencoders, intrinsic representations of the data was learned in an unsupervised manner. Then, soft-max activation function was used for hyperspectral classification . Results were competitive with other techniques.
Hatem Magdy Keshk et al [20]proposed deep neural network based method to obtain Super resolution (SR) images and satellite data was used to predict the performance of each deep learning based model. Cascading based deep network model outperformed other.
Theodosia Vardoulaki et al [21]proposed a methodto exploit information both from maps and from very high resolution google images. A patch-based, deep learning model was trained alongsidefive land cover classes and accuracy of 95% was achieved. R. Priyanka Iyer et al [22]provided an overview of hyperspectral image analysis and processing based on remote sensing.

CONCLUSION

In this literature review we studied various concepts of remote sensing image classification to achieve good quality images so that high accuracy can be achieved.From this study it was concluded that traditional methods used geometric uniqueness for identifying any object and poorly handles noisy data and missing data problems.Recent development of hyperspectral sensorsis a new technology with regard to detection and identifications..Deep learning in remote sensing is open tool box that provides opportunities for development of new applications.

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