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A STUDY OF DEEP LEARNING DATASETS AND MODEL IN REMOTE SENSING IMAGES CLASSIFICATION

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Abstract
The remote sensing Images Classification plays a vital role of real time applications and Deep Learning massive growth in dissimilar domains such as NLP, Computer Vision and medical fields. Compared to the machine Learning algorithms, deep networks provide higher accuracy and also strong ability to learn for data extraction. Geographical satellite pictures that are utilized for the investigation of environmental and geological fields are acquired through remote sensing techniques. The crude pictures gathered from the satellites are not appropriate for factual examination and precise report arrangement so raw images undergo the traditional image classification techniques such as data preprocessing, segmentation, data feature extraction and classification. The old image classification methods have spatial and spectral resolution problems. This problem can be solved by deep learning techniques. A new image classification method ,namely Convolutional Neural Networks(CNN) techniques . A noteworthy endeavors have been taken to build up an assortment of datasets, Deep learning Models and furthermore to show various methodologies that utilization these datasets for remote sensing images classification.

Keywords--- CNN, Classification, Deep Learning Models, Deep Learning Datasets, Remote Sensing images

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INTRODUCTION

The Remote sensing is the way toward checking a remote item without having a physical contact with that objects. The objects are gathering information utilizing the Artificial satellites that are propelled to spin around the earth. Earth Observation is a procedure of social event the data about planet Earth through remote sensing. The area, where we can gather the most information about our planet, whether estimating, horticulture, natural disaster, petroleum derivative and minerals recognizable proof, mapping of the land use, etc. The heavenly body satellites create the top notch pictures of the whole earth in a less measure of time. The pictures delivered by the topographical satellites have a lot of commotion and unessential information because of the interruptions caused in the space. Remote detecting is routinely depicted by complex data properties as heterogeneity and class inconsistency, and covering class unforeseen allocations. Together, these points of view comprise genuine challenges for making land spread maps or recognizing and limiting things, making a significant level of powerlessness in obtained results, despite for the best performing models.

The term Hyper spectral imaging goes under Spectral imaging. Hyper spectral imaging is the social occasion and handling of data from over the electromagnetic range. The other worldly design is the principle factor that separates hyper spectral symbolism from multispectral imagery. Hyper spectral symbolism contains groups with slender wavelengths while multispectral symbolism contains groups with wide wavelengths. The upside of utilizing hyper spectral information over. Multispectral information is the capacity to characterize surface highlights with a higher unearthly resolution. Recent mechanical advances in microelectronics have likewise spiraled into the satellite assembling industry. The scaling down of space grade segments has brought about the ascent of little satellites, including an extraordinary number of remote detecting satellites. With diminished dispatch and assembling costs, this has incited a democratized access to space. Thusly, satellite imaging (a subset of remote sensing) has encountered an expansion in intrigue and request over the latest couple of years, with symbolism so far accessible just to not many research bunches turning out to be significantly more openly available.

Learning Types

The Machine Learning have 3 major types
1. Supervised.
2. Unsupervised.
3. Reinforcement.

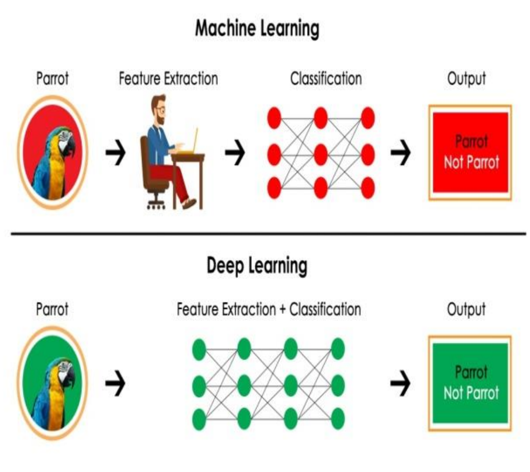

Figure 1. ML and DL Sample

1) Supervised learning: The algorithms uses the training data and feedbacks its helps to learn a relationship of inputs and desired outputs. Supervised algorithms help to predicts the output from the given information. it grouped into classification and regression problems.

a) Classification: result variable is a category, such as “red” or “green” or “dog” and “no dog”.
b) Regression: result variable is a real value, such as “dollor” or “coin”.
2) Unsupervised learning: All given information is unlabeled and the algorithms learn to the intrinsic structure from the given information. Identified the pattern and structure. Types. Clustering and Association
3) Reinforcement learning: Trained to the map action-to-situation, classifier is not programmed directly , trial and error.

Deep Learning Works
1. Data Collection
Assortment of data is one of the major and most significant assignments of any AI ventures. Since the data we feed to the calculations is data. Thus, the calculations productivity and accuracy relies on the rightness and nature of data gathered. So as the data same will be the yield.

2. Data preprocessing
Gathering the data is one undertaking and making that data helpful is an-other crucial assignment. Data gathered from different methods will be in a sloppy arrangement and there might be part of invalid qualities, in-legitimate data esteems and undesirable data. Cleaning every one of these data and supplanting them with proper or inexact data and evacuating invalid and missing data and supplanting them with some fixed interchange esteems are the essential strides in pre handling of data. Indeed, even data gathered may contain totally trash esteems. It may not be in careful arrangement or way that is intended to be. Every single such case must be confirmed and supplanted with interchange esteems to make data meaning significant and valuable for further preparing. Data must be kept in a composed organization.

3. Testing and Training
At last in the wake of handling of data and preparing the following undertaking is clearly trying. This is the place execution of the calculation, nature of data, and required yield all shows up out. From the enormous data collection gathered 80 percent of the data is used for preparing and 20 percent of the data is held for testing. Preparing as talked about before is the way toward making the machine to learn and giving it the capacity to make further forecasts dependent on the preparation it took. Though testing methods previously having a predefined data collection with yield likewise recently named and the model is tried whether it is working appropriately or not and is giving the correct expectation or not. On the off chance that most extreme number of forecasts are correct, at that point model will have a decent accuracy rate and is dependable to proceed with generally better to change the model.

4. Deep Learning Algorithm
The subsequent stage is calculations are applied to data and results are noted and watched. The calculations are applied in the design notice in the graph to improve accuracy at each stage.

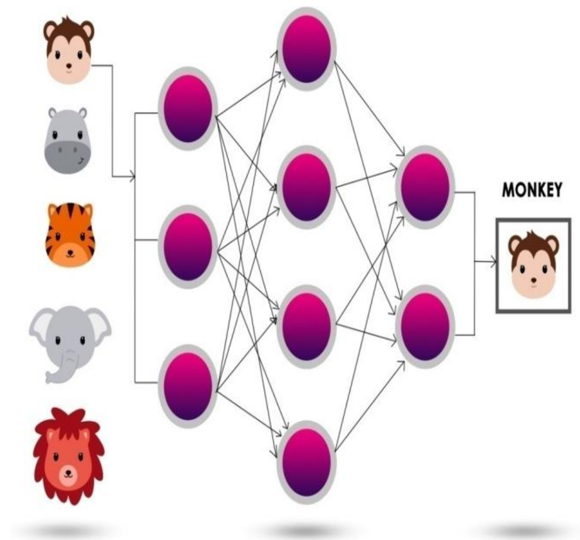

Figure 2. Deep learning working sample

CNN
The neural systems exploit the hidden structure in images. Topological information, i.e., spatial information about the structure in an image, for example, contiguousness and cycles are additionally considered. presently investigate the subtleties of how the various layers of a convolution neural system interact with each other.

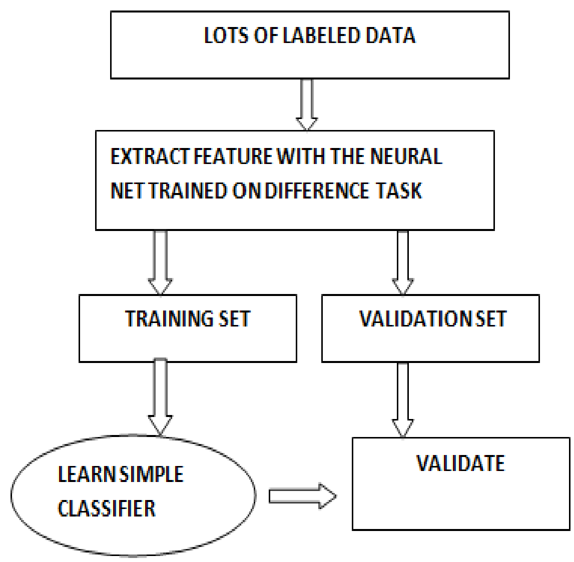

Figure 3. Deep Learning Flow diagram

LITERATURE SURVEY

S. NO	AUTHOR(s)	YEAR	TECHNIQUES /ACCURACY LEVEL
1	Cansu et.al [2]	2010	Viola-Jones Approach Accuracy (Ac) 0:9930
2	Nesrine Chehata , et.al[3]	2011	Object-Based, Multitemporal Classification. Overall Accuracy Was Of 87.2%

3	Daxiang Zhang, et.al[4]	2012	Object Based Method. Overall Accuracy Was Of 93.33%
4	Sophie Sauvagnargues , et.al[5]	2013	The Orfeo Toolbox (Otb). Overall Accuracy About 87%
5	Mariano R. et.al[6]	2013	Resource Selection Analysis (RSA), Accuracy : 81.1%
6	Minakshi Kumar et.al[7]	2013	Image Processing Technique. Accuracy 95%.
7	Charles Joseph Hanley et.al[8]	2015	Object Based Extraction Accuracy 89%
8	Reshma Suresh Babu, et.al[9]	2016	Road Extraction Techniques
9	Sandra Heleno, et.al[10]	2016	Gram–Schmidt Method Accuracy :77 %
10	L.Chaouche Ramdane, et.al [11]	2016	Multi-Resolution Approach Accuracy : 98%
11	K. Joshil Raj et.al[12]	2016	Bio Inspired Algorithms (BIA) Accuracy 94.5 %
12	Zhiyong Lv 1, et.al[13]	2017	MLC, NBC, SVM, Accuracy : Above 90 %
13	Bakhtiar Feizizadeha, et.al[14]	2017	Fuzzy Synthetic Evaluation (FSE) Approach. Accuracy :93.87 %
14	Maher Ibrahim Sameen et.al[15]	2017	Two-Stage Optimization Strategy Accuracy : 76 %
15	Valentine Lebourgeois ,Stéphane et.al	2017	Segmentation Algorithm. Accuracy : 91.7 %

DEEP LEARNING CONVOLUTIONAL NEURAL NETWORK MODELS AND DATSETS

1) AlexNet: The convolution layer is actualized by the information which is tangled with a lot of channel. The non-straight capacity is used to create a gathering of highlight. The maximum pooling layer is utilized to maximal estimations of spatially progressive nearby locales on the component maps to extricate the yield.

2) CaffeNet: The Caffe model gives a total toolbox to preparing, testing, fine-tuning, and sorting out models, with well documented. Simultaneously, it's conceivable the snappiest accessible execution of these calculations, making it in a flash important for mechanical organization

.

3) Google Net Going Deeper with Convolutions additionally called Google Net. I) by utilizing channels of various sizes at each layer, it reviews increasingly precise spatial information. ii) it altogether diminishes the quantity of free parameters of the network, making it less arranged to overfitting and enabling it to be more profound. Beginning modules are utilized within the all convolutions layer by utilizing corrected straight actuation.

4) VGGNet-16 VGGNet has two surely understood models: VGGNet-16 and VGGNet-19. In this estimation[15], its utilized the previous one due to its more straightforward structure and to some degree better execution. This model had three stages first stage 13 convolutional layers, second stage 5 pooling layers, and third stage 3 completely associated layers. The VGGNet-16 CNN highlight was likewise take out from the second completely associated layer to get a component vector of 4,096 measurements.

5) Places Net, has a comparable design with Caffe Net. The profound highlights from Places Net are more powerful in perceiving common scenes than profound highlights from convolution neural network prepared on Image Net. We will compute Places Net to affirm whether it brings about exceptional execution.

6) VG GNet To evaluate the presentation of various profound convolution neural network structure and partner them on a shared opinion, created three convolution neural network models dependent on the Caffe toolbox, every one of which finds a not a similar speed/accuracy.

7) Inception-v3 Inception-v3 is extra Image Net-improved structure. It is built up by Google and has a solid significance on making scaling to profound networks computationally proficient. The Inception model takes in 299 x 299 pictures for this methodology.

8) ResNet-50 ResNet-50 network is set up by Microsoft Research utilizing a structure that utilizations lingering capacities to which help to add impressive security to profound networks. It assess 18-layer and 34-layer leftover nets (ResNets).

The gauge structures associations are added to each match of 3X3 filters .Res Net diminishes the best 1 blunder by, coming about because of the adequately decreased preparing error.ResNet-50 is the 50-layer variant of ResNet. ResNet utilizes 224 x 224 pictures for this network.

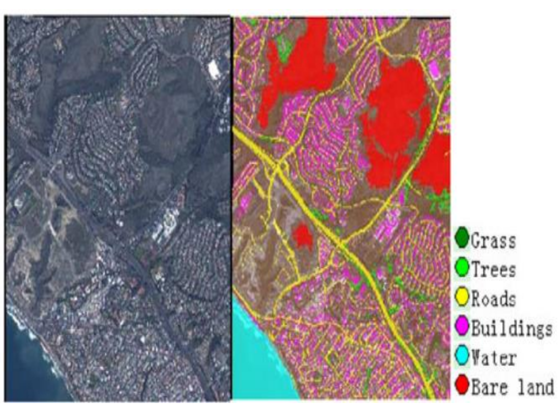

Figure 4. Satellite Image Sample Classes

Table 2. Accuracy level comparison of Optimization Techniques

Algorithm/tools	Classification	Accuracy Level
Cuckoo search algorithm	Per Pixel	0.94
ACO2/PSO 25	Per Pixel	0.97
Rough Set ,BBO	Object Based	0.67
ACO2/PSO , BBO	Per Pixel and Object	0.98
Fuzzy , BBO	Object	0.69
ACO , SOM	Object	0.70
ACO,BBO	Object	0.76
FPAB , BBO	Object	0.67
Ant Miner , BBO	Object	0.97
ABC , BBO	Object	0.91
AIN	Per Pixel	0.86

Figure 5. Sample Remote sensing Images

Table 3. Sample Dataset for Remote sensing Images Classification

S.No	Data Set	Total Image	Image Per Class	Scene Class	Image Per Size
1	SAT-4	50,000	100,00	4	28X28
2	IMAGENET	14000	2	2	256X256
3	UC MERCED LAND USE	2100	100	21	256X256
4	EUROSAT	27000	2000	10	64X64
5	WHU-RS	50	50	19	600X600
6	RSSCN7	400	400	7	400X400
7	SPACENET	17355	50	1	650X650
8	SAT-6	405,00	32400	6	28X28
9	BRAZILIAM COFFEE SCENE	2876	1438	2	64X64
10	SIRI-WHU	2400	200	12	200X200
11	RSC11	1232	10	11	512X512

QUANTITATIVE EVALUATION METRICS FOR DEEP LEARNING

Quantitative evaluation based on three matrices

1. Accuracy
2. Precision

2. Recall

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}}$$

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

CONCLUSION

An wide comparative survey given on various methodologies available in deep learning techniques and models. Also in this paper analyzing the difference literature gap for deep learning techniques and models. In this paper provides quantitative metrics like accuracy, precision, recall for evaluate the satellite images. All the supplementary information will be extremely much useful for image classification and identification of images .Its help the users to learn significant feature representations.

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