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Remote Sensing Data Analysis in Machine Learning and Proposed Quantum Computational Intelligence: A Meta-Analysis

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Abstract: Deep learning and machine learning are the top ranking techniques applied in objects classification in remote sensing data. We have conducted a meta-analysis and find out that feature selection is an important achievement in Machine Learning algorithms however, the following challenges were identified; Machine learning need large datasets for training and satellite images contain a lot of noise which may be classify as an object so it is not suitable for object detection in satellite images, Detection accuracy in machine learning depend on the quality of training datasets and finally Biased feature selection may led to the incorrect classification of objects in satellite images. While Most of the deep learning techniques suffer from data preprocessing problems especially when applying in satellite images because satellite images contain a lot of noise. Therefore the requirement of quality and quantity of training datasets is very high. The designed, development, improvement and adjustment of deep learning techniques to suit a specific research is still rely on the experience of the developer which is also a challenging issue. Application of deep learning techniques in remote sense data are still in an infant state because based on our review only few numbers of articles are published from Africa countries. We have suggested that quantum computational intelligence to be applied in remote sensing data analysis.

Keywords: Deep Learning, Machine Learning, Satellite Image, Quantum Computational Intelligence, Remote Sensing

1. Introduction

Remote sensing technology is recently used to capture accurate information for different variety of application such as weather and climate changes, urban and rural area detection, water body and snow detection, scene classification etc. American society for photogrammetry and remote sensing defined remote sensing as the" measurement or acquisition of information of some property of an object or phenomenon by a recording device that is not in physical contact with the object or phenomenon under study" [1].

The standard sensors used in remote sensing includes; Spectral and Hyper spectral Sensor, Radio Detection and Ranging (RADAR) sensor, Light Detection and Ranging (LIDAR) and Thermal Infrared Detectors. These are all used in satellites or suborbital aircraft such as airplane, helicopters and unmanned aerial vehicle (UAV). Most of these sensors recorded electromagnetic radiation (EME) that travel at a velocity of $3X10^8$ ms^{-1} from the source either directly through a vacuum space or indirectly through reflection or re-radiation to the sensor. The interesting features of this instrument is that there is no actual distance between the device and the object to be captured it could be 100m, 200m or even millions of meters.

Many countries are deeply involved in launching of remote sensing satellites since early 1960s, recently some developed countries has the capability of sending more than one satellite in one mission for instance in 2013 USA lunched 29 satellites, in 2015 Russia lunched 37 satellite, in the same year China lunched 20 satellites and in 2016 India lunched 20 satellites at a time [2]. Remote sensing satellite are classified based on orbital geometry and timing this includes; Geostationary, equatorial and Sun-synchronous orbits. Geostationary satellite has a period of 24 hours to make a complete rotation equal to the earth, it is mostly used for communication and weather forecasting. Equatorial orbit it make a cycle in a low inclination while sun-synchronous with a very high inclination angle [3]. There are many remote sensing satelslites for environmental monitoring this includes; LandSat, IKONS, QuickBird, WorldView, CryoSat, SIRAL, Sentinel, SPOT, CHAMP, TerraSAR-X, CBERS, ZY-102C, ZY-3, HJ-1A/B, HJ-1C, GF-1, Jilin-1, JERS-1 and Resurs-F etc.

2. Quantum Computational Intelligence

Quantum computational intelligence algorithms such as quantum artificial neural networks, quantum artificial immune system, quantum fuzzy logic, and quantum swarm intelligence, quantum neuro fuzzy quantum probabilistic algorithm and so on by combining the complex quantum properties which includes, entanglement and superposition and the sensitivity of computational intelligence algorithm to formulate a heterogeneous system.

In the concept of information theory and quantum information the smallest unit are bit while in quantum is known as Qubit which were represented as Boolean in computing and represented as a neuron in neuro- computing, in fuzzy logic is either 0 or 1, and in digital electronics is either on and off. Which are also represented as Boolean state 0 and 1 and orthogonal quantum states labeled as $|0\}$ and $|1\}$ respectively in the quantum state are represented as a superposition $\propto |0\} + B\,|1\}$ where $\propto, B \in C$ satisfy normalization.

Let consider a computer quantum system, that consist of the qubits and the state of each of this qubit is called superposition which is also represented as;

$$|\Psi\} = C_0|0\} + C_1\,|1\} \tag{1}$$

Where $|0\}$ and $|1\}$ are the called vectors and C_0, C_1, $\in C$, by combining the two qubits and analyze the system as one would have a possible state of the two qubits as;

$$|\Psi\} = \frac{|0\}|0\} + |1\}|1\}}{\sqrt{2}} \tag{2}$$

Then notation $|U\}$ and $|V\}$ are the breakdown of $|U\}$ and $|U\}$ in the quantum state and are called bell which represent the major property that shows there is no single qubit state $|a>$ and $|b>$ such that $|\Psi >= |a\}|b\}$ hence the following are possible.

$$|\Psi\} = |a\}|b\} = (ao\,|o\} + a1|1 > (bo|0\} + b1\,|1\} = ao\,bo|0\}|0\} + a, b, |1\}|1\} + ao\,b1\,|0\}|0\} + a1\,b1|1\}|0\} \tag{3}$$

While the general state of a bipartite quantum system can be defined as;

$$\phi = \alpha\,|00\} + \beta\,|01\} + \lambda\,|10\} + \delta\,|11\} \tag{4}$$

The above computation can be applied to remote sensing.

3. Machine Learning

Machine learning (ML) is a branch of artificial intelligence that enable computer algorithm to learn from training datasets. This learning are categorized into three forms supervised, semi-supervised and unsupervised, supervised learning means the training inputs are given and the mapping between the input and the desired outputs are known and also the mapping between the input and outputs are learned by the algorithm. In unsupervised learning the inputs are given but the algorithm learn and identify pattern and produce the output, however, in semi-supervised learning the inputs and the outputs are partially given and the algorithms will find the missing pattern based on the inputs features [4].

Machine learning techniques are commonly applied to object detection in satellite images such as support vector machine is commonly applied techniques for to object classification in satellite images these are earlier proposed in [5] applied in change detection, more over another traditional object classification techniques is called K-Nearest-Neighbor (KNN) are applied to object classification in remote sensing images In addition to Artificial Neural Network (ANN) that are also applied in remote sensing data such as object detection, classification and change detection as presented in [6].

Table 1. *Deep learning techniques applied to object detection.*

S/N	Authors/Date	Research Title	Problem Addressed	Method Used	Weakness of the Method
1.	Alshehhi *et al.*, (2017) [7]	Simultaneous extraction of roads and buildings in remote sensing imagery with convolutional neural networks	Road extraction	Convolutional neural network	Computational complexity is high in this method and very difficult to adjust the network
2.	Ajeet *et al.*, (2018) [8]	Application of deep learning for object Detection	Object detection	Deep learning	Data preprocessing problem and require large data for training
3.	Absalberg, (2015) [9]	Detection of seals in remote sensing images using features extracted from deep convolutional neutral networks	Seal detection	Convolutional neural network	Inadequate datasets for training
4.	Abhishek *et al.*, (2021) [10]	Deep learning for object detection and Scene perception in self-driving cars	Scene perception in self driving cars	Deep learning	Data preprocessing problems
5.	Arshitha & Biju, (2020) [11]	Accurate detection of building from satellite images using CNN	Building detection	Convolutional neural network	Un able to differentiate between shadow and building
6.	Ahmad *et al.*, (2019) [12]	Small Objects Detection in Satellite Images Using Deep Learning	Object detection	Deep learning	In adequate datasets and training objects are too much
7.	Alexander, *et al* (2020) [13]	Semantic segmentation of Aerial imagery for road Extraction with deep learning	Road extraction	Deep learning	Segmentation accuracy depend on the design and adjustment of the network

S/N	Authors/Date	Research Title	Problem Addressed	Method Used	Weakness of the Method
8.	Boualleg & Farah, (2018) [14]	Enhanced interactive remote sensing image retrieval with scene Classification convolutional neural networks model.	Scene classification and image retrieval	Convolutional neural network	Low retrieval rates due to the complexity of the network
9.	Chen *et al* (2017) [15]	Deep learning-based classification of hyper spectral data.	Image classification	Deep learning	Data preprocessing problem
10.	Chen, *et al* (2015) [16]	Spectral-spatial classification of hyper spectral data based on deep belief network.	Image classification	Deep belief network	Unable to classify image with background
11.	Cheng, *et al.,* (2016) [17]	Scene classification of high resolution remote sensing images using convolutional neural networks.	Scene classification	Convolutional neural network	Inadequate datasets
12.	Claudia, *et al.,* (2020) [18]	Satellite image processing to detect building using deep Learning	Building detection	Deep learning	Unable to differentiate between shadow and building
13.	Castelluccio, *et al.,* (2015) [19]	Land use Classification in Remote Sensing Images by convolutional Neural Networks.	Land used classification	Convolutional neural network	Unable to differentiate between vegetation areas as land used
14.	Duan, *et al* (2017) [20]	SAR image segmentation based on convolutional-wavelet neural network and Markov random field	Image segmentation	Convolutional wavelet neural network	Inadequate datasets
15.	Deepthi *et al*. (2021) [21]	Detection and classification of Objects in Satellite Images using CNN	Object detection and classification	Convolutional neural network	Complexity of the network make it very difficult to adjust the network
16.	Deng, *et al* (2011) [22]	Multi-scale object detection in remote sensing imagery with convolution neural networks.	Object detection	Convolutional neural network	Low accuracy obtained
17.	Duarte, (2018) [23]	Satellite image classification of building damages using air bone and satellite image sampling in deep learning approach.	Detection of damaged building	Deep learning	Data preprocessing problem
18.	Erhan *et al*. (2014) [24]	Scalable object detection using deep neural networks.	Object detection	Convolutional neural network	Inadequate datasets
19.	Feng, *et al*. (2019) [25]	Water body extraction from very high resolution remote sensing imagery using deep U-net and super-pixel based conditional random field model.	Water body extraction	Deep neural network	Complexity in mathematical interpretation make it very difficult to differentiate between road channel and water body
20.	Gao, *et al*. (2019) [26]	Road extraction from high resolution remote sensing imagery using refined deep residual convolutional neural network	Road extraction	Deep residual convolutional neural network	Data preprocessing problem
21.	Gao, *et al*. (2017) [27]	Dual-branch deep Convolution neural network for Polari metric SAR image classification.	Image classification	Deep convolutional neural network	Computational complexity problems
22.	Ghamisi, *et al*., (2016) [28]	A Self-improving convolution Neural network for the classification of hyper spectral data.	Image classification	Convolutional neural network	Require large amount of data for training
23.	Geng, *et al*. (2015) [29]	High-resolution SAR image classification via deep convolutional auto-encoders	Image classification	Deep convolutional auto-encoder	Data preprocessing problems
24.	Geng, *et al*. (2017) [30]	Deep supervised and contractive neural network for SAR image classification.	Image classification	Deep supervised learning	Required large amount of labeled datasets for training the model
25.	Guoji *et al*. (2020) [31]	Water identification from high resolution remote sensing image based on multidimensional densely connected convolutional neural networks.	Water identification	Densely connected convolutional neural network	Cannot differentiate between water body and snow
26.	Gao, *et al*. (2019) [32]	Road extraction from high-resolution remote sensing imagery using refined Deep Residual Convolutional neural network	Road extraction	Deep residual convolutional neural network	Cannot differentiate between road channel and water channel
27.	Zhang, *et al*. (2018) [33]	An object-based convolutional neutral networks (OCNN) for urban land use classification.	Land used classification	Object based convolutional neural network	Unable to differentiate land and mountain
28.	Zou *et al*. (2015) [34]	Deep Learning based feature selection for remote Sensing scene classification.	Scene classification	Deep learning	Unable to classify all the objects in the image due to the complexity in satellite image

4. Conclusion

Deep learning, machine learning are the major techniques applied in object classification in remote sensing image. We have conducted a meta-analysis and find out that feature selection is an important achievement in Machine Learning algorithms applied in computer vision however, the following challenges are identified:

Machine learning require large data for training and satellite images contain a lot of noise which may be classify as an object so it is not suitable for object detection in satellite images.

Detection accuracy in machine learning depend on the quality of training datasets.

Biased feature selection may led to the incorrect classification of objects in satellite images.

Deep Learning techniques has an automatic ability to learn from the feature sets for several task and has been the major breakthrough in recent time with a successful applications in computer vision and image processing. Despite the tremendous advancement achieved in deep learning techniques the following challenges need serious attention;

Deep learning techniques are much dependent on large amount of data for training and testing to avoid over fitting. The time taken for feature extraction in remote sense data with deep neural networks for object detection is also a challenging task in computer vision. Many efforts are required to further improve the computational efficiency of the model.

Computational complexity of deep learning techniques which require large amount of system memory to process is also a challenging issue.

Most of the deep learning techniques suffer from data preprocessing problems especially when applying in satellite images because satellite images contain a lot of noise. Therefore the requirement of quality and quantity of training datasets is very high.

The designed, development, improvement and adjustment of deep learning techniques to suit a specific research is still rely on the experience of the developer which is also a challenging issue.

Application of deep learning techniques in remote sense data are still in an infant state because based on our review only few number of articles are published from Africa countries.

5. Recommendations

Based on this research work it is recommended that quantum computing should be applied heavenly in remote sensing data analysis which is a road map for further research directions.

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