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Advances in Scene Classification of Remotely Sensed High Resolution Images and the Existing Datasets

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Abstract*: Research on Scene classification of remotely sensed images has shown a significant improvement in the recent years as it is used in various applications such as urban planning, urban mapping, management of natural resources, precision agriculture, detecting targets etc. The recent advancement of intelligent earth observation system has led to the generation of high resolution remote sensing images in terms of spatial, spectral and temporal resolutions which in turn helped the researchers to improve the performance of Land Use Land Class (LULC) Classification Techniques to a higher level. With the usage of different deep learning architecture and the availability of various high resolution image datasets, the field of Remote Sensing Scene Classification of high resolution (RSSCHR) images has shown tremendous improvement in the past decade. In this paper we present the different publicly available datasets , various scene classification methods and the future research scope of remotely sensed high resolution images.

***Index Terms*: Deep Learning, Remote Sensing, Scene Classification, Datasets, Convolutional Neural Networks.**

I. INTRODUCTION

The term Remote Sensing refers to the observation of earth surface from a distance apart i.e. from a remote area. The Remote Sensing images can either be a satellite images or aerial images observed by a satellite or airborne vehicles. Earlier the remote sensing images are of low resolution where the pixel itself would be in the size of object of interest and therefore it laid more limitation in classification techniques with pixel based approach.

Due to the availability of high resolution images, researchers started exploring spatial pattern (patterns created by pixels) based approach for object identification and classifications. Example house, tree, road etc. The Spatial pattern based approach was not able to provide semantic information of the images as each pixel or sub pixel in a image might have some semantic meaning. With the advancement of Machine learning, researchers started concentrating on new classification technique based on semantic level classification technique known as Remote Sensing Scene Classification(RSSC).

Scene Classification is the process of assigning each scene image to a semantic label i.e. to a predefined land use land classification (LULC) class. For example commercial building, airport, park, school , agricultural area, mountain etc. Here the Scene images are the local image patches which is derived manually from a larger remotely sensed images that contain specific semantic classes[13-26].

Earlier the scene classification was implemented using Bag Of Visual Words(BOVW) approach where the potential for improving the design of feature extractor is limited. In the recent years with the implementation of deep convolutional network[21-25], RSSC has attained a state of art performance using the publicly available datasets.

This paper aims at providing the basic ideas and concepts behind remote sensing scene classification using deep learning and to provide the direction of investigations for the researchers who are at initial stage of their research. The remaining paper is organised as follows. Section II - Datasets for Remote Sensing Scene Classification, Section III - Remote Sensing Scene Classification Methods, Section IV - Future Research Direction and Section V - Conclusion.

II. DATA SETS FOR REMOTE SENSING SCENE CLASSIFICATION

There are many publicly available datasets for Remote Sensing Scene Classification used for research purpose with varied no of classes, spatial resolution and size. Mostly used datasets are listed below.

A. UC-Merced Land-Use[1]

This is the mostly used dataset in RSSC since 2010. The source of this dataset is "United States Geological Survey National Map" covers some of the areas in US. It contains 21 image classes for land use ('airplane', 'agricultural', 'baseball diamond', 'buildings', 'beach', 'chaparral', 'dense residential', 'freeway', 'forest', 'harbour', 'golf course', 'intersection', 'mobile home park', 'medium density residential', 'parking lot', 'overpass', 'river', 'sparse residential', 'runway', 'tennis court' and 'storage tanks') . This dataset contains some highly overlapped classes, which makes the classification task highly challenging and therefore it is extensively and mostly used for research purpose in RSSC.

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Table 1 : The Publicly Available Datasets For Remote Sensing Scene Classification:

Sl No	Dataset	Total Images	Image Classes	No Of Images Per Class	Spatial Resolution in m	Image Size	Year
A	UC-Merced Land-Use [1]	2100	21	100	0.3	256 X 256	2010
B	WHU-RS19[2]	1005	19	50(approx)	0.5 and less	600 X 600	2012
C	SIRI-WHU[3]	2400	12	200	2	200 x 200	2016
D	RSSCN7	2800	7	400	No fixed resolution	400 x 400	2015
E	RSC11	1232	11	100(approx)	0.2	512 x 512	2016
F	Pattern Net[4]	30400	38	800	0.06 to 4.7	256 x 256	2017
G	NWPU-RESISC45[5]	31500	45	700	0.2 to 30	256 x 256	2017
H	RSI - CB128[6]	> 36000	45	Varies between 198 - 1331	0.3 to 3	128 x 128	2017
I	RSI-CB256[6]	> 24000	35	Varies between 173 - 1550	0.3-3	256 X 256	2017
J	AID[7]	10000	30	Varies between 173 - 1550	0.5 - 0.8	600 x 600	2017
K	AID++[8]	> 400000	46	Relatively higher no of images per class.	Variable higher resolution.	512 x 512	2018

B. WHU-RS19[2]

The dataset **WHU-RS19[2]** is extracted from Google Earth. It contains 19 classes ('beach', 'airport', 'bridge', 'football field', 'commercial area', 'forest', 'desert', 'industrial area', 'farm land', 'meadow', 'park', 'mountain', 'parking lot', 'port', 'pond', 'railway station', 'river', 'residential area' and 'viaduct'). It has a varied resolution, image illumination, scale and orientation which makes the classification task challenging and therefore it is also used in RSSC. But the no of images per classes are less compared to UC-Merced dataset.

C. SIRI-WHU[3]

This Dataset **SIRI-WHU[3]** is also extracted from Google Earth and covers only some of the urban areas in China. It has only 12 image scene classes ('agriculture', 'harbour', 'commercial', 'industrial', 'idle land', 'park', 'meadow', 'pond', 'overpass', 'water', 'residential' and 'river'). As this dataset contains lesser no of scene classes and does not contain diversity , limits the usage of this dataset in RSSC.

D. RSSCN7

This Dataset is also extracted from Google Earth and it has seven scene classes ('grass land', 'forest', 'farm land', 'parking lot', 'residential region',' industrial region', and 'river/lake'). It does not have a fixed resolution. They are extracted with four different scales which makes it more challenging for RSSC.

E. RSC11

This is a High Resolution dataset exported from Google Earth and covers many well known cities in Unites States such as New York, Washington DC, San Francisco, Los Angles, Houston, Chicago and San Diego. It contains 11 scene classes, that has more similar vision images, which makes it more complicated and challenging for classification ('dense forest', 'sparse forest', 'grass land', 'storage tanks', 'harbour', 'residential area', 'high buildings', 'roads', 'low buildings', 'railway' and 'overpass')

F. Pattern Net[4]

This dataset is extracted from Google Earth that covers some of the cities in US with various resolution and contains 38 scene classes('airplane', 'base ball field', 'basket ball court', 'beach', 'bridge', 'cemetery', 'chaparral', 'Christmas tree farm', 'closed road', 'coastal mansion', 'cross walk', 'dense residential', 'ferry terminal', 'football field', 'forest', 'freeway', 'golf course', 'harbour', 'intersection', 'mobile home park', 'nursing home', 'oil gas field', 'oil well', 'over pass', 'parking lot', 'parking space', 'railway', 'river', 'runway', 'runway marking', 'shipping yard', 'solar panel', 'sparse residential', 'storage tank', 'swimming pool', 'tennis court', 'transformer station' and 'waste water treatment plant'). It has 800 images per class which makes it a larger database compared to previous datasets. The features such as large scale, high resolution , higher intra class diversity and higher inter class similarity makes it more challenging and therefore it can be extensively used for RSSC.

G. NWPU-RESISC45[5]

This dataset is extracted studying other previous datasets. It is a larger dataset with variable resolution and hence it became the benchmark dataset in RSSC. It contains 45 scene classes ('airport', 'airplane', 'basket ball court', 'base ball diamond', 'golf course', 'beach', 'chaparral', 'bridge', 'church', 'cloud', 'circular farm land', 'commercial area', 'desert', 'dense residential', 'forest', 'freeway', 'ground track field', 'industrial area', 'harbour', 'intersection', 'island', 'mobile home park', 'lake', 'medium residential', 'meadow', 'mountain', 'palace', 'over pass', 'parking lot', 'railway station', 'railway', 'rectangular farm land',

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'river', 'roundabout', 'runway', 'snow berg', 'sea ice', 'sparse residential', 'ship', 'stadium', 'tennis court', 'storage tank', 'terrace', 'wetland' and 'thermal-power-station'). It has 700 images per class.

H. RSI - CB128 and RSI-CB256[6]

RSI-CB is extracted from Google Earth and Bing Maps with 0.2m-3m spatial resolution. RSI-CB128 has 128x128 pixel size and RSI-CB256 has 256x256 pixel size therefore the researchers can select the dataset according to their depth of Classification model.

RSI-CB128 has 45 classes ('turning circle', 'town', 'tower', 'stream', 'storage room', 'sparse forest', 'snow mountain', 'shrub wood', 'sea', 'sapling', 'sand beach', 'river protection forest', 'river', 'residents', 'rail', 'pipeline', 'parking lot', 'over pass', 'natural grass land', 'mountain road', 'mountain', ' marina', 'mangrove', 'lakeshore', 'hirst', 'highway', 'green farm land', 'grave', 'fork road', 'forest', 'dry farm', 'desert', 'dam', 'cross road', 'container', 'coast line', 'city road', 'city green tree', 'city building', 'city avenue', 'bridge', 'bare land', 'avenue', 'artificial grass land', 'airport run way')

RSI-CB256 has 35 classes ('town', 'stream', 'storage room', 'sparse forest', 'snow mountain', 'shrub wood', 'sea', 'sapling', 'sand beach', 'river protection forest', 'river', 'residents', 'pipeline', 'parking lot', 'mountain', 'marina', 'mangrove', 'lakeshore', 'hirst', 'highway', 'green farm land', 'forest', 'dry farm', 'desert', 'dam', 'cross road', 'container', 'coast line', 'city building', 'bridge', 'bare land', 'avenue', 'artificial grass land', 'airport run way', 'airplane')

I. AID[7]

Aerial Image Dataset (AID) is also one of the recent large scale bench mark dataset extracted from Google Earth and contains 30 aerial scene classes. ('viaduct', 'stream', 'storage tank', 'square', 'sparse residential', 'school', 'river protection forest', 'river', 'railway station', 'resort', 'port', 'pond', 'play ground', 'parking', 'park', 'mountain', 'meadow', 'medium residential', 'industrial', 'forest', 'farm land', 'dense residential', 'desert', 'commercial', 'centre', 'church', 'bridge', 'beach', 'base ball field', 'bare land', 'airport'). AID is multi-source unlike UC-Merced and samples are taken from different regions like Unites States, China, Italy, France, England, Germany etc at different times and seasons. It has high intra class variations, smaller inter class dissimilarity and larger scale dataset which makes the classification task challenging and attracts more researchers.

J. AID++[8]

This is the latest large scale aerial image dataset that consist of 4,00,000 images distributed in 46 classes('airport', 'runway', 'bridge', 'parking', 'parking by the road', 'road', 'viaduct', 'port', 'railway station', 'beach', 'lake', 'river', 'bare land', 'desert', 'ice',' rock', 'mountain', 'mix resident', 'multi-family', 'single family', 'dry land', 'paddy fields', 'terraces', 'meadow' , 'shrub', 'forest', 'solar power station', 'wind power station', 'hydraulic power station', 'storage tanks', 'work factory', 'mine', 'oil field', 'commercial', 'church', 'base ball field', 'basket ball field', 'golf course', 'stadium', 'soccer field', 'tennis court', 'cemetery', 'amusement park', 'park', 'pool', 'square') . This was constructed by (i) forming a category network which is derived by using available geodatabases (Google Map API and Open Street Map) to obtain the category coordinates, (ii) querying and then downloading the images by using those coordinates, (iii) manually eliminating the annotation errors to scale up the dataset and (iv) improving the separation between similar classes. This is the most powerful dataset as it has largest no of images that can be deployed in training deep CNN extensively and thereby helps in RSSC.

III. REMOTE SENSING SCENE CLASSIFICATION METHODS

Many scene classification techniques using aerial and satellite images have been proposed in the last decade. The process of Scene Classification consist of two steps i.e. Feature extraction and then Classification based on the extracted features. Therefore an effective representation of features is required to develop a high performance Remote Sensing scene Classifier. There are three main types of scene classification techniques based on the features of scene image namely the traditional RSSC using handcrafted Feature, RSSC using unsupervised feature learning(UFL) and RSSC based on Deep Learning.

A. Handcrafted Feature[15] Based RSSC Methods:

In Handcrafted Feature Based RSSC Methods, the classification is based on handcrafted features. These methods requires extracting human engineering skills based features such as colour, shape, spectral resolution, spatial resolution, size and texture etc. The classification was based on these features individually or by combining some of the features. And based on it, various classification techniques were proposed such as colour histograms , GIST, texture descriptors , scale-invariant-feature-transform(SIFT) , and histogram of the oriented gradients (HOG). The main drawback in this method is the difficulty in obtaining the discriminative features in a challenging scene image datasets.

B. Unsupervised Feature Learning Based RSSC Methods[13,14]:

The limitation of handcrafted feature based method was overcome by UFL Based RSSC Methods where the required features are automatically extracted from the scene image. Some examples of this methods are Principal Component Analysis, K means clustering, sparse coding and auto encoders. This method performed better than handcrafted feature based methods, but failed to give a state of art performance as this method was not able to provide best discriminative features between the classes due to lack of semantic information's provided by the category label.

C. Deep Learning based classification methods[16-26]:

In the last decade various Deep Learning based classification methods were then developed by researchers which were capable of learning the discriminative features on its own using deep learning neural network architectures. The unsupervised feature learning architectures has a shallow architecture whereas deep learning uses multi layered architecture, therefore it has a powerful feature learning capability. So it is capable of extracting the hidden information's and discriminative features of multi dimensional data's. The semantic features of the data are also observed in the top layers itself.

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All these factors led the successful implementation and state of art performance of deep neural networks architecture in semantic level scene classification.

RSSC using CNN: Though there are many deep learning architecture, the CNN architecture is the predominant architecture used for classification techniques.

CNN proved to be successful in classifying challenging large scale variant image datasets using efficient high performance GPUs. The CNN process the input in the form of multi dimensional arrays. For example RGB spectral band Image consist of three 2D arrays, similarly multi spectral image consist of multiple 2D arrays.

Basically CNN architecture consist of the following main layers.

(i) Convolutional layers extracts the low level features at the initial layers and then the more discriminative and expressive features are obtained as the depth of the layers increases.

(ii) Pooling layer is used to reduce the size of the representations i.e. down sampling and also to speed up calculations, as well as to make some of the features it detects to be a bit more robust. It is of two types - Maxpooling and Average pooling. Stride, size and types are the hyper parameters of pooling.

(iii) Fully connected layers are the last few layers of the network where they process the information from lower layers and feed them to the output layers to make decisions.

Overfitting is one of the major problem in Convolutional Neural Networks which has to be sorted out by proper design. Another main issue in classification is lesser no of images in the training dataset which can be rectified to some extend by Data Augmentation technique. Data Augmentation can be defined as the way to create new data from the existing data by different orientation techniques. It also prevents overfitting problems. Mirroring, Random Cropping, Scaling, Rotation, Shearing, Local warping and colour shifting are some of the data augmentation methods.

CNN Architectures: Some of the CNN Architectures which has shown state of art performance in RSSC are

(i) Alexnet[9] was proposed in the year 2012 consists of approximately 60 million parameters for the purpose of classification.

(ii) VGGNet[10] - VGG-16 was proposed in the year 2014 has almost 16 trainable layers. The advantages of using this architecture are it can have up to 138 million parameters, simplicity, reduced dimension and increased depth.

(iii) ResNet[11] - The previous deep neural networks are harder to train and the training error starts to raise again as the number of layers increase and also due to Exploding and vanishing gradients problem. All this problems were overcome by Resnet which implemented skip connection i. e. the output of one layer is fed to the input of deeper layers. ResNet (Residual Network), was proposed in the year 2015. The advantage of using this networks are the efficient performance with very deep network , less computational cost and ability to train very deep network in a effective manner.

(iv) GoogLeNet[12] is a inception network module that was proposed in the year 2014, which has 9 inception modules. In Inception network , the network can decide the suitable filter size on its own from the given choices. Therefore the computational cost is reduced.

Recent Research works in RSSC[21-25]: Various research works has been proposed for RSSC[16-20]. The existing deep learning methods for scene classification will be based either by using pretrained network or by making the pretrained model adapt or by training new networks. Fine tuning the pretrained CNN networks showed a greater performance. In some models the activation is directly taken as image representation from fully connected layers . In some of the models dicriminative features are extracted by encoding CNN activations from convolutional in feature coding scenarios. Here the convolutional features maps are viewed as a 2-D array of local features. In general, all the above model were able to provide state of art performance using the publicly available high resolution datasets.

The year 2018 showed a major breakthrough in RSSC. Various RSSC techniques were proposed. We list here a few. (i) RSSC by concatenation of the global features and the rearranged local features[21]. (ii) RSSC by fusion of features of the same Image with different scale[23]. (iii) RSSC by extracting intermediate level features to prevent overfitting and performing the fusion by analyzing canonical correlation to obtain more powerful discriminative features[22,24]. (iv) RSSC by concentric circle pooling to avoid rotation invariant problem[25].

Capsule Network (CapsNet)[26], is a novel network architecture which has become the active research area in classification for the past two years. Here the term capsule refers to the group of neurons or vectors used as input. It is capable of exploiting the properties and spatial information of features in the image to a greater extend and thereby gives an efficient output performance. It is expected that Capsule network will soon replace the traditional CNN architecture though still under research.

IV. FUTURE RESEARCH DIRECTION

Developing a Improved Datasets: Almost all of the research on scene classification aims at improving the accuracy using the existing datasets. And we can say that it has reached a saturation level due to the limitation of available dataset. The deep learning architectures are more powerful with millions of parameters which does not match with the quantity of datasets used. For practical implementation the available datasets are not enough i.e. we require a enormous amount of data "Big data". So we expect the research community to develop a high quality and high quantity challenging datasets in the coming years which is capable for real world applications. And new algorithms for classification of this datasets can be developed.

Fusion of Remote Sensing data with Social Media data: There are lot of data coming from social media such as facebook, twitter, instagram which can give a better understanding of the image scene of interest. Scene Classification by combining the remote sensing images with this social media information using suitable deep learning architecture can provide us with an improved state of art performance for real time application in the coming years.

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Scene Classification With Caption: Another possible research direction is instead of simply classifying the image scene with their class, we can try to describe the scene of interest. The description can contain the details about the objects present in the scene, the size of the objects, their orientation details, texture, reason for it to be classified in to a particular scene category etc. Combination of Image scene classification models with image scene captioning can give better understanding of the image scene.

V. CONCLUSION

In this paper we have discussed the basic ideas and concepts behind RSSC of HR image datasets and also provided the direction of investigations for the researchers to move on. We have summarised the different publicly available datasets for classifications with their merits and demerits. The advancement of scene classification techniques from the traditional BOVW methods to Deep learning methods were also discussed. Then the Scene classification techniques based on CNN model was discussed along with their architectures. The Capsnet architecture and Recent Research works in RSSC were also briefed. And At last we have also provided the Future research ideas for RSSC. Hope that the research community of RSSC gets benefitted by this paper and they also share their research ideas.

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