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Satellite And Land Cover Image Classification Using Deep Learning

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Abstract: Satellite imagery is important for many applications including disaster response, law enforcement and environmental monitoring. These applications require the manual identification of objects and facilities in the imagery. Because the geographic expanses to be covered are great and the analysts available to conduct the searches are few, automation is required. Yet traditional object detection and classification algorithms are too inaccurate and unreliable to solve the problem. Deep learning is a family of machine learning algorithms that have shown promise for the automation of such tasks. It has achieved success in image understanding by means of convolutional neural networks. The problem of object and facility recognition in satellite imagery is considered. The system consists of an ensemble of convolutional neural networks and additional neural networks at integrate satellite metadata with image features.

1. INTRODUCTION

Deep learning is a class of machine learning models that represent data at different levels of abstraction by means of multiple processing layers. It has achieved astonishing success in object detection and classification by combining large neural network models, called CNN with powerful GPU. A CNN is a deep learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a CNN is much lower as compared to other classification algorithms. While in primitive methods filters are hand engineered, with enough training, CNN have the ability to learn these filters/characteristics. The architecture of a CNN is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlaps to cover the entire visual area. CNN-based algorithms have dominated the annual ImageNet Large Scale Visual Recognition Challenge for detecting and classifying objects in photographs. This success has caused a revolution in image understanding, and the major technology companies, including Google, Microsoft and Facebook, have already deployed CNN-based products and services.

A CNN consists of a series of processing layers as shown in Fig. 1.1. Each layer is a family of convolution filters that detect image features. Near the end of the series, the CNN combines the detector outputs in fully connected “dense” layers, finally producing a set of predicted probabilities, one for each class. The objective of the convolution operation is to extract the high level features such as edges, from the input image. CNN need not be limited to only one Convolutional Layer. Conventionally, the first CNN is responsible for capturing the Low-Level features such as edges, color, gradient orientation, etc. With added layers, the architecture adapts to the High-Level features as well, giving us a network, which has the wholesome understanding of images in the dataset, similar to how we would. Unlike older methods like SIFT and HOG, CNNs do not require the algorithm designer to engineer feature detectors. The network itself learns which features to detect, and how to detect them, as it trains.

LITERATURE SURVEY

[1]In this paper, we propose a multiscale deep feature learning method for high-resolution satellite image scene classification. Specifically, we first warp the original satellite image into multiple different scales. The images in each scale are employed to train a deep convolutional neural network (DCNN). However, simultaneously training multiple DCNNs is time-consuming.

To address this issue, we explore DCNN with spatial pyramid pooling (SPP-net). Since different SPP-nets have the same number of parameters, which share the identical initial values, and only fine-tuning the parameters in fully connected layers ensures the effectiveness of each network, thereby greatly accelerating the training process. Then, the multiscale satellite images are fed into their corresponding SPP-nets, respectively, to extract multiscale deep features.

[2] Semantic segmentation of remote sensing images enables in particular land-cover map generation for a given set of classes. Very recent literature has shown the superior performance of deep convolutional neural networks (DCNN) for many tasks, from object recognition to semantic labelling, including the classification of Very High Resolution (VHR) satellite images. However, while plethora of works aim at improving object delineation on geographically restricted areas, few tend to solve this classification task at very large scales. New issues occur such as intra-class class variability, diachrony between surveys, and the appearance of new classes in a specific area, that do not exist in the predefined set of labels

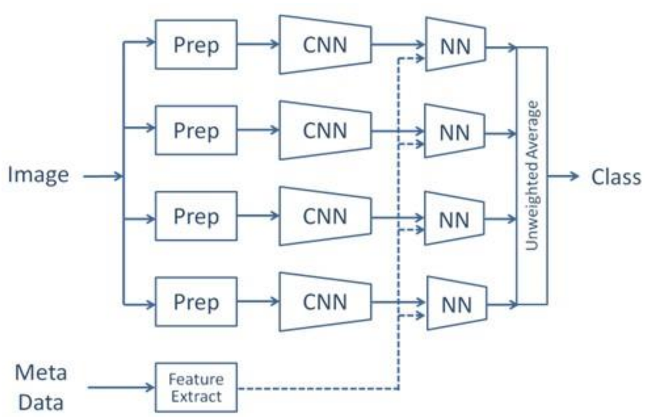
[3] In this study, stacked autoencoders which are widely utilized in deep learning research are applied to remote sensing domain for hyperspectral classification. High dimensional hyperspectral data is an excellent candidate for deep learning methods. However, there are no works in literature that focuses on such deep learning approaches for hyperspectral imagery. This study aims to fill this gap by utilizing stacked autoencoders. Experiments are conducted on the Pavia University scene. Using stacked autoencoders, intrinsic representations of the data are learned in an unsupervised way. Using labeled data, these representations are fine tuned. Then, using a soft-max activation function, hyperspectral classification is done. Parameter optimization of Stacked Autoencoders (SAE) is done with extensive experiments. Results are competitive with the state-of-the-art techniques.

EXISTING SYSTEM AND ITS DRAWBACKS

In existing system, the satellite images are stored and object classification is done through primitive object detection techniques. The main problem faced by this technique is the updating of images. Because the geographic expanses to be covered are great and the analysts available to conduct the searches are few then an automation is required. Yet traditional object detection and classification algorithms are too inaccurate and unreliable to solve the problem. The techniques without using deep learning is time consuming process. And also the images with similar structure may be confusing for the traditional system. So chances for wrong results are large

PROPOSED SYSTEM AND ITS ADVANTAGES

The proposed system is a deep learning system that classifies objects and facilities in highresolution multi-spectral satellite imagery.



A. Fig:4.2.1 System architecture

The system consists of an ensemble of CNNs with post-processing neural networks that combine the predictions from the CNNs with satellite metadata. Combined with a detection component, the system could search large amounts of satellite imagery for objects or facilities of interest.

IMAGE PREPARATION

The first step that has to be performed is image preparation. This is a most important step because any small changes from this step can cause a vital change to overall output. Initially, images in the dataset may contain different sizes and resolution. Therefore, images had to be resized before training. Because every image has to be considered within a common frame. And also, for the easiness of processing the images in the dataset it must have same range of resolution. Then only the training phase will become accurate. For that a bounding box is required. These images in the dataset have to be preprocessed for extracting the features from it.

Each and every image is considered using this bounding box, so the feature extraction from these images will become more precise. Each image will consider using a bounding box then it squares the bounding box to preserve the aspect ratio of the image features by expanding the smaller dimension to match the larger dimension. The part lies outer to the bounding box will get cropped. Such image resizing occurs. And it has to be also noted that every image that has been given for training must be of same range of resolution. After these steps a square image will get. Feature extraction using CNN will happens with this square image. The image will get looped using CNN and other part of the image will also considered as a loop.

Fig:6.1.1 Image preparation

CNN

After image preparation, the resized images enter the CNN. CNN is mainly used for enabling looping structure to the image. For providing proper looping and feature extractions bottleneck layers are implemented. A bottleneck layer is a layer that contains few nodes compared to the previous layers. It can be used to obtain a representation of the input with reduced dimensionality. So, the image can be process up to several levels, which increases its accuracy. It is the last pre-processing phase before the actual training with data recognitions start. It is a phase where a data structure is formed from each training image that the final phase of training can take place and distinguish the image from every other image used in training material.

CONCLUSION

The proposed method shows a deep learning system that classifies objects and facilities in high resolution multi-spectral satellite imagery. The system consists of an ensemble of CNNs with deep learning libraries that combine the predictions from the RF algorithm with satellite metadata. Combined with a detection component, the system could search large amounts of satellite imagery for objects or facilities of interest. In this way it could solve the problems in various fields. By monitoring a store of satellite imagery, it could help law enforcement officers detect unlicensed mining operations or illegal fishing vessels, assist natural disaster response teams with the mapping of mud slides or hurricane damage, and enable investors to monitor crop growth or oil well development more effectively

FUTURE ENHANCEMENT

This proposed work uses images that have been already taken by any satellite. So the images may be taken before a long time can challenge the security. For that to enable accuracy and security live streaming from satellite can be enabled by using high quality cameras. The proposed work is based on images, but it can also extend for videos taken by satellite by using efficient streaming equipment.

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