

Satellite and Land Cover Image Classification Using Deep Learning

Roshni Rajendran¹, Liji Samuel²

M. Tech Student, Department of Computer Science and Engineering, Sree Buddha College of Engineering, Kerala, India¹

Assistant Professor, Department of Computer Science and Engineering, Sree Buddha College of Engineering, Kerala, India²

ABSTRACT:Satellite imagery is vital for several applications including disaster response, enforcement and environmental monitoring etc. These applications require the manual identification of objects within the imagery. Because the geographical area to be covered is extremely large and therefore the analysts available to conduct the searches are few, thus an automation is required. Yet traditional object detection and classification algorithms are too inaccurate and unreliable to unravel the matter. Deep learning may be a part of broader family of machine learning methods that have shown promise for the automation of such tasks. it's achieved success in image understanding by means of convolutional neural networks. the matter of object and facility recognition in satellite imagery is taken into account. The system consists of TensorFlow libraries and random forest algorithm for classification.

KEYWORDS:Deep Learning, Convolutional neural network, VGG, GPU, TensorFlow.

I. 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. CNN-based algorithms have dominated the annual ImageNet Large Scale Visual Recognition Challenge for detecting and classifying objects in photographs. 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 [1]. 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 network itself learns which features to detect, and how to detect them, as it trains.

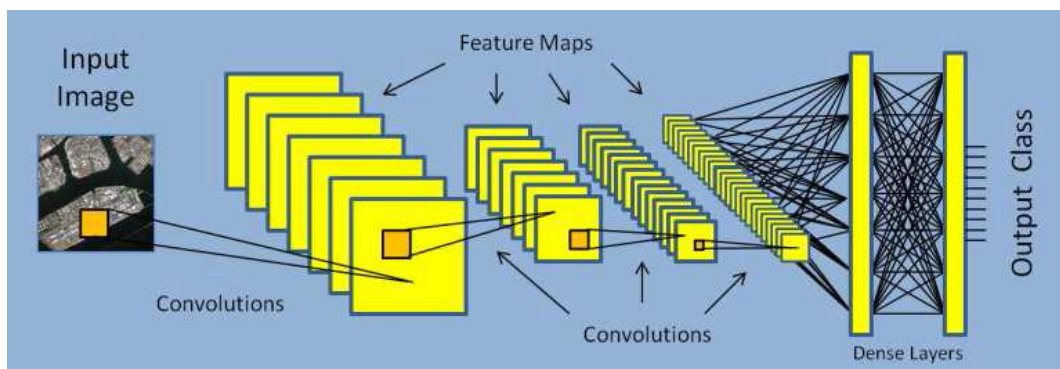


Fig:1 Architecture of satellite image classification

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. But traditional object detection and classification algorithms are too inaccurate and unreliable to solve the

problem. Deep learning can be used to understanding the image by means of convolutional neural networks. The system consists of an ensemble of CNNs along with image preparation operations that combine the image features from the CNNs with the image metadata. The ensemble merges the outputs of the NNs by means of unweighted averaging into a set of prediction probabilities for the classes. The maximum probability determines the classification. The output of the system is a satellite image along with metadata. The system is implemented in Python using the Random Forest algorithm, Xamp and TensorFlow deep learning libraries.

Paper is organized as follows. Section II describes the related work about the proposed system. Section III describes the steps include image classification. Section IV presents experimental results showing results of images tested. Finally, Section V presents conclusion.

II. RELATED WORK

Liang Zhang et al. [2] says that in the field of aerospace measurement and control field, optical equipment generates a large amount of data as image. Thus, it has great research value for how to process a huge number of image data quickly and effectively. With the development of deep learning, great progress has been made in the task of image classification. The task images are generated by optical measurement equipment are classified using the deep learning method. Firstly, based on residual network, a general deep learning image classification framework, a binary image classification network namely rocket image and other image is built. Secondly, on the basis of the binary cross entropy loss function, the modified loss function is used to achieves a better generalization effect on those images difficult to classify. Then, the visible image data downloaded from optical equipment is randomly divided into training set, validation set and test set. The data augmentation method is used to train the binary classification model on a relatively small training set. The optimal model weight is selected according to the loss value on the validation set. This method has certain value for exploring the application of deep learning method in the intelligent and rapid processing of optical equipment task image in aerospace measurement and control field.

T. Postadjiana et al. [3] proposes that supervised classification is the basic task for landcover map generation. From semantic segmentation to speech recognition deep neural networks has outperformed the state-of-the-art classifiers in many machine learning challenges. Such strategies are now commonly employed in the literature for the purpose of land-cover mapping. The system develops the strategy for the use of deep networks to label very high resolution satellite images, with the perspective of mapping regions at country scale. Therefore, a super pixel based method is introduced in order to (i) ensure correct delineation of objects and (ii) perform the classification in a dense way but with decent computing times.

Chaomin Shen et al. [4] discuss that the percentage of cloud cover is one of the key indices for satellite imagery analysis. To date, cloud cover assessment has performed manually in most ground stations. To facilitate the process, a deep learning approach for cloud cover assessment in quicklook satellite images is proposed. Same as the manual operation, given a quicklook image, the algorithm returns 8 labels ranging from A to E and *, indicating the cloud percentages in different areas of the image. This is achieved by constructing 8 improved VGG-16 models, where parameters such as the loss function, learning rate and dropout are tailored for better performance. The procedure of manual assessment can be summarized as follows. First, determine whether there is cloud cover in the scene by visual inspection. Some prior knowledge, e.g., shape, color and shadow, may be used. Second, estimate the percentage of cloud presence. Although in reality, the labels are often determined as follows. If there is no cloud, then A; If a very small amount of clouds exist, then B; C and D are given to escalating levels of clouds; and E is given when the whole part is almost covered by clouds. There is also a label * for no-data. This mostly happens when the sensor switches, causing no data for several seconds. The disadvantages of manual assessment are obvious. First of all, it is tedious work. Second, results may be inaccurate due to subjective judgement.

Qingshan Liu et al. [5] discuss about a multiscale deep feature learning method for high-resolution satellite image scene classification. However, satellite images with high spatial resolution pose many challenging issues in image classification. First, the enhanced resolution brings more details; thus, simple lowlevel features (e.g., intensity and textures) widely used in the case of low-resolution images are insufficient in capturing efficiently discriminative information. Second, objects in the same type of scene might have different scales and orientations. Besides, high resolution satellite images often consist of many different semantic classes, which makes further classification more

difficult. Taking the commercial scene comprises roads, buildings, trees, parking lots, and so on. Thus, developing effective feature representations is critical for solving these issues.

III. IMAGE CLASSIFICATION METHODOLOGY

The framework comprises of a gathering of CNNs alongside picture arrangement activities that consolidate the picture highlights from the CNNs with the picture metadata. The gathering blends the yields of the NNs by methods for unweighted averaging into a lot of expectation probabilities for the classes.

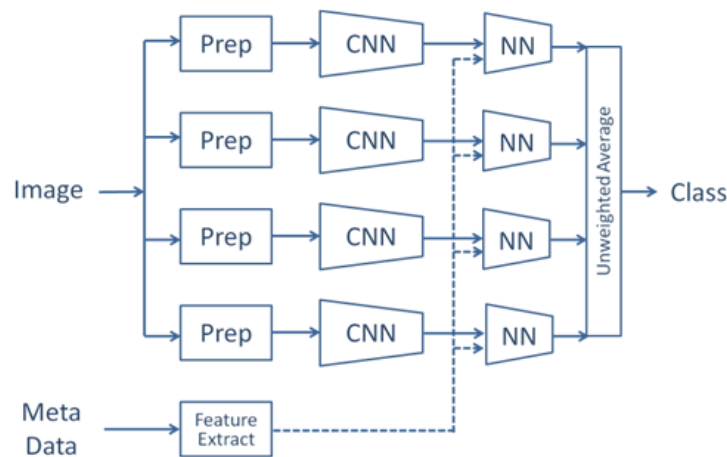


Fig:2Image preprocessing and classification

The maximum probability determines the classification. The output of the system is a satellite image along with metadata. The system is implemented in Python using the Random Forest algorithm, Xamp and TensorFlow deep learning libraries. Each process can be explained in details below.

DATASET

The first task is to collect the dataset. Since due to various security issues, live satellite image is not accessible. So we are using aerial images of various types of land. All these images are meant to be in same range of resolution. It is to the easiness of training. All the images are accessed through google search.

TRAINING

It is common practice in machine learning to split the data into a training set and a validation set. The purpose is to provide data to train the neural networks yet reserve a subset to ensure that they do not over-fit to the training data. A 70% of input dataset is taken for training and 30% is taken for validation.

For training TensorFlow is used. A default inception model is downloaded first. And later it is customized with the help of dataset. A CNN layer is used where it will transform the dataset to a text file which contains the feature coordinates of the image. Each input image is frozen and looped to extract the feature coordinates with the help of CNN. Using this difference between the images in a folder is checked to review the accuracy of the input data. Based on this text file an inference graph is generated which is further used to loading into TensorFlow.

CLASSIFICATION

The classification of images is done by using an algorithm called Random Forest. This algorithm provides a divide-and-conquer approach of decision trees generated on a randomly split dataset. The input image will be provided by the user. The dataset is already processed and stored as a compressed file called inception model. The construction of decision trees are done between this input image and the training dataset. This collection of decision trees is known as the forest. Each tree votes and the most popular class is chosen as the final result. That is decision trees are

constructed with the input data. For construction of decision trees a looping is required, for that CNN is used. The layer of CNN depends on how many input data classes we own. The prediction results are got from each of the decision tree. For those tree which have the maximum probability value is considered and its root node will be the final class.

IV. EXPERIMENTAL RESULTS

The figure shows the images from the training dataset. The aerial images of airbase and basketball court is considered. Figs. (a) shows the aerial image of an airbase, (b) and (c) shows the aerial image of basketball court. The first step is to train the dataset using TensorFlow. Then inception model will be generated. This model will be kept for the further classification using algorithm.



(a)



(b)



(c)

It is very important to keep proper images for dataset. Because what is training in this phase will affect the accuracy of the output. So, building a precise and correct dataset is very important.

V. CONCLUSION

Various methods to capture and identify the objects in the satellite imagery are analysed. Each of them works with different schemes. Each scheme varies on the convolution layers used and also their application used. A deep learning system that classifies objects in the satellite imagery is considered. 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, this system could search large amounts of satellite imagery for objects or facilities of interest. This system is still developing and a detailed working procedure will be acknowledged later.

Analysing satellite imagery has very important role in various applications such as it could help law enforcement officers to 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.

REFERENCES

- [1] M. Pritt and G. Chern, "Satellite Image Classification with Deep Learning," *2017 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*, Washington, DC, 2017, pp. 1-7.
- [2] L. Zhang, Z. Chen, J. Wang and Z. Huang, "Rocket Image Classification Based on Deep Convolutional Neural Network," *2018 10th International Conference on Communications, Circuits and Systems (ICCCAS)*, Chengdu, China, 2018, pp. 383-386.
- [3] T. Postadjian, A. L. Bris, C. Mallet and H. Sahbi, "Superpixel Partitioning of Very High Resolution Satellite Images for Large-Scale Classification Perspectives with Deep Convolutional Neural Networks," *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*, Valencia, 2018, pp. 1328-1331.
- [4] C. Shen, C. Zhao, M. Yu and Y. Peng, "Cloud Cover Assessment in Satellite Images Via Deep Ordinal Classification," *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*, Valencia, 2018, pp. 3509-3512.
- [5] Q. Liu, R. Hang, H. Song and Z. Li, "Learning Multiscale Deep Features for High-Resolution Satellite Image Scene Classification," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 56, no. 1, pp. 117-126, Jan. 2018.
- [6] Roshni Rajendran | Liji Samuel "Satellite Image Classification with Deep Learning: Survey" Published in *International Journal of Trend in Scientific Research and Development (ijtsrd)*, ISSN: 2456-6470, Volume-4 | Issue-2, February 2020
- [7] P. Helber, B. Bischke, A. Dengel and D. Borth, "Introducing Eurosat: A Novel Dataset and Deep Learning Benchmark for Land Use and Land Cover Classification," *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*, Valencia, 2018, pp. 204-207.
- [8] K. Cai and H. Wang, "Cloud classification of satellite image based on convolutional neural networks," *2017 8th IEEE International Conference on Software Engineering and Service Science (ICSESS)*, Beijing, 2017, pp. 874-877.
- [9] A. O. B. Özdemir, B. E. Gedik and C. Y. Y. Çetin, "Hyperspectral classification using stacked autoencoders with deep learning," *2014 6th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)*, Lausanne, 2014, pp. 1-4.