IP TERM PROJECT

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INTRODUCTION

In machine learning, a convolutional neural network (CNN, or ConvNet) is a class of deep, feed-forward artificial neural networks that has successfully been applied to analyzing visual imagery.

CNNs use a variation of multilayer perceptrons designed to require minimal preprocessing.[1] They are also known as shift invariant or space invariant artificial neural networks, based on their shared-weights architecture and translation invariance characteristics.

Convolutional networks were inspired by biological processes in which the connectivity pattern between neurons is inspired by the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field.

CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage.

They have applications in image and video recognition, recommender systems and natural language processing.

- DESIGN MODEL

Apart from the methods to detect splicing, we tried our hands-on experience with Convolutional Neural Network. It is made up of neurons that have learnable weights and biases. The input consists of images. The layers of a ConvNet have neurons arranged in 3 dimensions: width, height, depth. (Note that the word depth here refers to the third dimension of an activation volume.) .

A simple ConvNet is a sequence of layers, and every layer of a ConvNet transforms one volume of activations to another through a differentiable function. We use three main types of layers to build ConvNet architectures: Convolutional Layer, Pooling Layer, and Fully-Connected Layer. Here also, we will stack these layers to form a full ConvNet architecture.

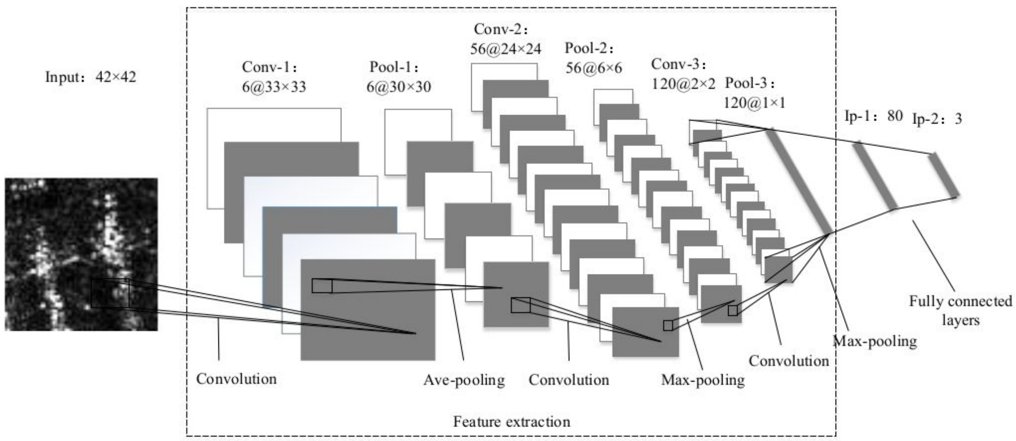

Figure 1. Architecture of CNN_{42}

DESCRIPTION

- OBJECTIVE

We address the problem of detecting the builtin areas from SAR images. To achieve the result we used multiscale CNN.

- DATASET

We were given the large SAR image from which we had to crop our dataset using QGIS. QGIS is a cross-platform free and open-source desktop geographic information system (GIS) application that supports viewing, editing, and analysis of geospatial data.

- MODEL DESCRIPTION

The model, as described in the paper, is a multi-scale CNN architecture. It has 3 sequential models merged together to form a better model. This is done to combine the robustness of models with low entropic capacity (CNN14 and CNN84 in our case) and the ability to learn higher contextual features from models with higher capacity, while preventing the overfitting problem.

Layer	CNN_{14}	CNN_{42}	CNN_{84}
Conv-1	8×8 60	10×10 6	7×7 6
Pool-1	4×4 60	4×4 6	4×4 6
Conv-2		7×7 56	7×7 60
Pool-2		4×4 56	3×3 60
Conv-3		5×5 120	
Pool-3		2×2 120	
Ip1	45	80	45
Ip2	3	3	3

After merging the 3 sequential models we are using a dense fully connected layer of size 120, with relu activation, for learning the features from the models. All the convolutional layers are followed by an activation layer (relu). This is used along with dropout technique to speed up training and to force the model to learn only 'robust' features.

SPECIFICATION OF THE SYSTEM

- SPECIFICATIONS OF THE SYSTEM USED

  24 processors - Intel(R) Xeon(R) CPU E5-2620 v3 @2.40GHz

  2 GPUs -

  - NVIDIA Quadro k620
  - NVIDIA Tesla K20Xm

- Python 3.1
- Anaconda
- Tensorflow
- Keras

EXPERIMENTAL RESULTS

Separately training the 3 models gives us the following results.

CNN14 = 62%

CNN42 = 64%

CNN84 = 62.5%

Multiscale = 69%

CONCLUSION

A model based on multiscale CNNs has been proposed to solve the problem of built-up areas detection in high-resolution SAR images. By combining with the great feature extraction ability of CNNs, we use multiscale CNNs to extract multiscale features to make a detection. The results from the experiment suggests that multiscale CNN model is effective to detect built-up areas in high-resolution SAR images.