Land Use and Land Cover Classification Using Deep Residual Network

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***Abstract*—Development activities have significant impact on topography. The estimation of land cover and use is important for the governmental bodies to effectively plan development stages in order to avoid degeneration of environmental quality and for ecological balance. The current datasets are either small-scale or have very high resolution, which takes time for processing. The supervised learning approaches to machine learning require large training datasets with adequate number of labels to predict the classes with good accuracy rates. In this project, we have implemented the research paper written by Patrick Helber, Benjamin Bischke, Andreas Dengel and Damian Borth in which they suggest the use of Sentinel-2 satellite images for the classification. The EuroSAT dataset has been derived from the satellite images dataset available freely for both commercial and non commercial use.**

I. Introduction

We are addressing the challenge of land use and land cover classification using images obtained from satellite. The images that we use for training and testing our model is taken from Sentinel-2 satellite images. We train our model in a way that we can correctly classify 6 labels: Forest, Highway, Industrial, Pasture, Permanent Crop and Residential. In the original paper there were 10 classes(which has additional classes like Sea lake, River, Herbaceous vegetation and Annual crop), which we reduced to 6 due to computational limitations. These labels obtained from classification describe the represented physical land type or how a land area is used.

This classification could help implement various applications in the field of agriculture, disaster recovery, urban development, climate change, environmental monitoring and many more. With the accuracy of classifying land cover with 98.61% in case of 6 classes and 92.46% in case of 10 classes, we are able to keep the geographical maps up-to date. One can monitor this data over a period of time, and detect changes in land use or land cover. For example, an image which showed an area as Forest few years ago, now shows Residential area, it would indicate Urban development. Similarly we could keep track of deforestation and afforestation by monitoring the land cover over a period of time, which could further help in analyzing climate change. Another application of this study would be Mapping. It could help keep the maps up-to date by providing data to open-sourced foundations like OpenStreetMap, which aims to support and enable the development of freely-reusable geo-spatial data.

Classifying images into various categories is the goal of scene classification. This is a very challenging problem, because land covers characterizing a given class may present a large variability and object images may be scale-variant and orientation-variant. This combined with the varying distance creates a problem that grows even more as finer classifications are sought. Here the same land covers and even the same objects can be found in images belonging to different classes. Many land cover classification algorithms have been developed, with solid theoretical foundations, based on spectral and spatial properties of the pixels. Algorithms like K-Means clustering are usually used to classify the images into labels. However, this task becomes more difficult as the level of abstraction increases, going from pixels, to objects, and then scenes. We use deep convolutional neural networks(CNN) to solve the remote sensing land cover scene classification task. Considering the similarities among categories in land cover classification, the advantage of deep learning with respect to descriptors using pixel based or object based approaches can be observed easily.

II. Related Work

The other research work to develop datasets for land cover and use estimation include UC Merced Land Use Dataset (UCM) which was introduced by Yang et. al. This dataset covers 21 classes and has 100 images of size 256X256 pixels for each class. The dataset, however intensively researched, is a very small data for accurate supervised learning. Other researchers have tried to use Google Earth images for classification. Processing images of high resolution to create a labeled dataset takes a lot of time.

III. What we did

In supervised machine learning, performance of classification systems strongly depends on the availability of high-quality datasets with a suitable set of labels, achieved by good classification model. We used deep Convolutional Neural Networks to train our model, to give us high classification accuracy. We started by converting the image dataset into required format using Image preloader, and then pre-processed the real-time images by zero sampling the images with the specified mean. Next we built our residual network by convoluting the input data with weighted decay of 0.0001. We have applied 32 layers in our residual blocks in order to build our Residual Network. We perform batch normalization to prevent neurons from saturating when input images have varying scale, and to aid generalization. Once the Residual Network is built, we perform Regression by adding a fully connected layer to the model. We then save the trained model in the specified path.

Designing a structure to create such a model was a challenging part of the project. Fine tuning feature values to preprocess real-time images, took us some time. Considering the recent success of deep CNN, it is crucial to have large quantities of training data available to train such a network. On obtaining the image set, our next task was to build residual network. We started by training the layers with a learning rate of 0.1 and later fine tuned and trained the entire network with a learning rate from 0.001 to 0.0001. Our Residual Network consists of 32 layers. The data set we downloaded for training and testing our model consisted of 27000 images. Training this dataset took a long time given the computational limitation. The training of our model took around 3 days at various epochs and learning rates.

We are using EuroSAT data set, based on satellite image data which is freely available for commercial and non-commercial use. It consists of 27,000 labeled images with 10 different classes and covers 13 spectral bands. The 10 different classes are Forest, Highway, Industrial, Pasture, Permanent Crop, Residential, Sea lake, River, Herbaceous vegetation and Annual crop.

IV. Results

- TensorBoard Graph
  Figure 1 shows the flow of our code that is generated

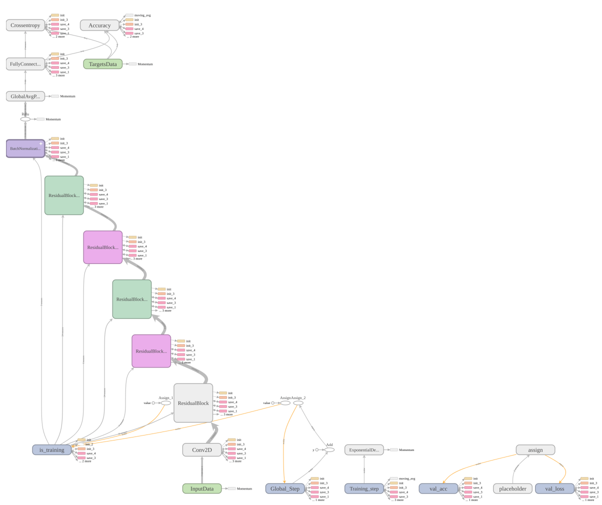

Fig. 1. TensorBoard Graph flow of code

  on the TensorBoard dashboard.

- Confusion Matrix
  Figure 2 shows the Confusion matrix with 10 classes

  (0:'Industrial', 1:'River', 2:'Forest', 3:'AnnualCrop', 4:'HerbaceousVegetation', 5:'Highway', 6:'Pasture', 7:'PermanentCrop', 8:'Residential', 9:'SeaLake)

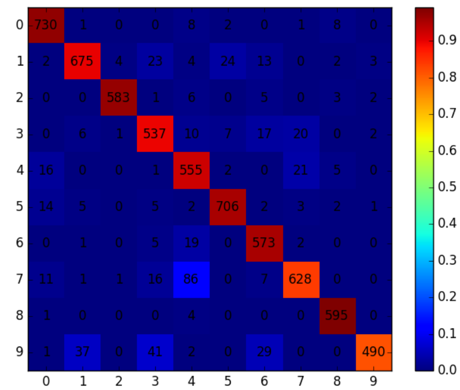

Fig. 2. Confusion matrix with 10 classes

- Accuracy Validation
  Figure 3 shows the Accuracy Validation with 10

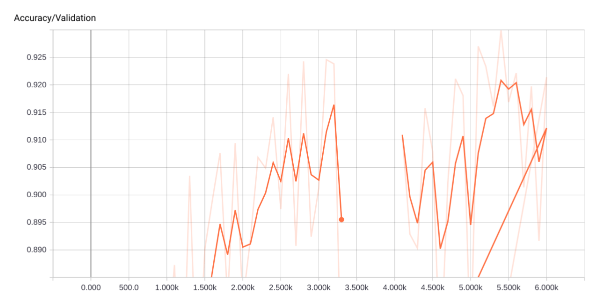

Fig. 3. Accuracy Validation

  classes

- Loss Validation
  Figure 4 shows the Loss Validation with 10 classes

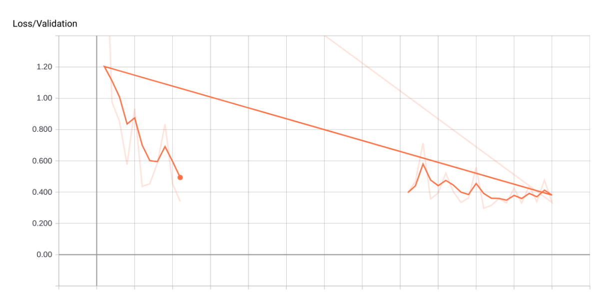

Fig. 4. Loss Validation

- Dataset
  Dataset used in the project can be downloaded from http://madm.dfki.de/files/sentinel/EuroSAT.zip . It consists of 27000 images.

V. Conclusion

We learned to train a deep CNN by supervised learning from EuroSAT dataset. We split the dataset in 70:30 ratio for training and testing, respectively. As we know, deeper neural networks perform better when the intermediate layers are normalized for convergence, we built a residual neural network with 32 layers in the residual blocks. We were expecting our network to classify for 10 classes with 98.57% accuracy, and we were able to train it for 6 classes with 98.61% accuracy and for 10 classes with 92.13% accuracy.

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