RAPID EARTHQUAKE DAMAGE DETECTION USING DEEP LEARNING FROM VHR REMOTE SENSING IMAGES

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ABSTRACT

Very High Resolution (VHR) remote sensing optical imagery is a huge source of information that can be utilized for earthquake damage detection and assessment. Time critical task such as performing the damage assessment, providing immediate delivery of relief assistance require immediate response; however, processing voluminous VHR imagery using highly accurate, but computationally expensive deep learning algorithms demands the High Performance Computing (HPC) power.

To maximize the accuracy, deep convolution neural network (CNN) model is designed especially for the earthquake damage detection using remote sensing data and implemented using high performance GPU without compromising with the execution time. Geoeye1 VHR disaster images of the Haiti earthquake occurred in year 2010 is used for analysis. Proposed model provides good accuracy for damage detection; also significant execution speed is observed on GPU K80 High Performance Computing (HPC) platform.

Index Terms— Deep learning, Deep CNN, GPU, damage detection, HPC

1. INTRODUCTION

Potential risk from a disaster can be minimized by developing satellite data processing applications for various phases of disaster such as disaster detection, prevention, disaster preparedness or disaster relief, rehabilitation, reconstruction after the occurrence of disaster. However, satellite data processing involves voluminous (Multispectral, Hyperspectral), variety (Airborne, space borne) of data with high velocity (high temporal resolution) hence referred to as "Big Data", but disaster related applications require near real time satellite data processing to provide immediate response. Also, applications cannot compromise with large data processing overhead, as it affects the accuracy, which should be maximized to avoid wrong decisions or false alarm.

To improve the accuracy of object detection, deep learning approaches are used extensively in current era and also observed as efficient in remote sensing domain [1][2][3][4]. General framework of deep learning approaches with varying deep learning methodologies, and its tuning tricks for remote sensing data are presented in [6]. Makantasis et al. [2] have applied deep CNN and Multi-layer perceptron (MLP) based on feed forward approach for classification of hyperspectral imagery using its spectral and spatial characteristics. Vakalopoulou et al. [4] have used deep learning approach for building detection from VHR multi-spectral images. Object characterization is very difficult and time consuming in traditional classification approaches such as Bayesian, decision tree, support vector machine etc.

Vetrivel et al. [5] have developed Deep CNN model for earthquake damage detection, however they have used the aerial and UAV dataset for training the model, they have observed around 90 ±3 % accuracy. As compared to arial / UAV imagery, Earth Observation (EO) satellites covers very large area and continuously monitors Earth unlike need-base survey using aerial and UAV technologies, also VHR satellite images are cost effective and quite capable of identifying the damaged region. There are several pre-trained model available such as UNET [11], VGGNet [12], Resnet etc. for deep learning, but to develop a robust network, full control on architecture layers and its parameters are essential.

This work focuses on development of fine-tuned deep CNN model design for damage classification. Though satellite data is too rich in terms of its contents, effective utilization of that data is lacking in handling critical events like disaster management etc. because of computationally expensive operations involved in it. Hence, the major objective of this work includes:

- Fine-tuned design of deep learning model for earthquake damage classification
- Parallel execution of deep learning model for earthquake damage detection using Google Colab platform on multicore K80 GPU [7]
- Evaluation of the model for speed and accuracy

2. REQUIREMENT FOR NEAR REAL TIME DISASTER DATA ANALYSIS

Satellites can observe a large geographic area which includes earthquake prone areas. It is possible in near future that the data captured by satellite can be processed in real time using onboard earthquake detection/monitoring system using high performance computing platforms such as GPU (recently embedded High performance computing platforms are emerging, which are small powerful devices capable of having many computing cores) as illustrated in figure 1, depending on the functionality implemented, in a couple of minutes, a near real time system will be capable of providing the notification about highly affected areas which can be used to plan medical emergency resource management. Onboard analysis can notify the pathway to reach to the affected area for relief supply and rescue system. Also, it will be capable of performing the damage assessment that provides information about losses, impacts of losses and will also help in decisions such as fund release/compensation.

A near real time system for disaster management should be capable of providing the following benefits:

- Prediction and notification of the extent of damage based on large amount of data from multiple sensors and processing it in near real time
- Monitoring of geographical changes and further impact of those changes based on huge temporal data
- Dynamic representation of analyzed data
- Easy interpretation and multi-dimensional visualization of the data

From the literature survey, it is noticed that damaged detection algorithms works well for VHR imagery whose resolution is around 1 meter to improve the accuracy, different types of features such as geometric features, texture features are obtained from pre and post disaster imagery and compared or classified to detect the damages; it is also mentioned in the work by Brunner et al. (2010) [8] that complete damages are difficult to discover using SAR imagery. Dell'Acqua et al. 2011 [12] have used both SAR and optical images (QuickBird PAN/MS images) for damage detection using texture parameters Mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, correlation; they have concluded that, optical images are more suitable for distinguishing damaged and undamaged data, however SAR data is useful for identifying type of damages such as low, heavy etc. They have classified the damages in five groups, totally collapsed, first or mid-story collapsed, damaged roof, lightly damaged roof, light damage where there is no visual changes in the roof.

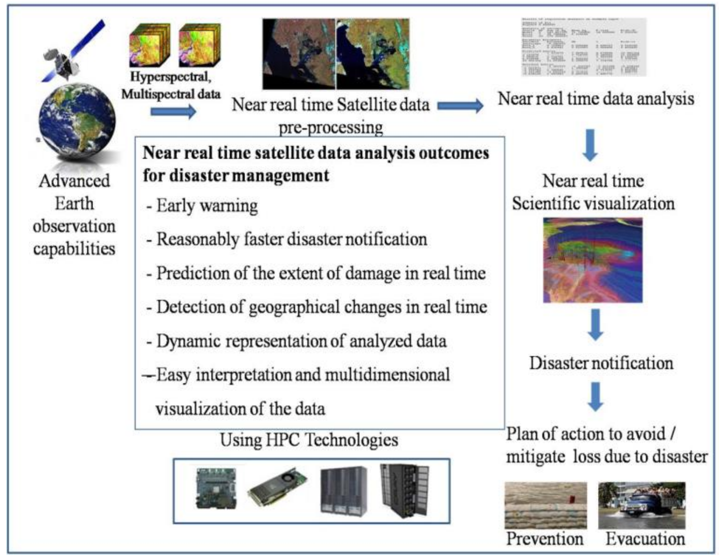

Figure 1 Real time satellite data processing requirements for disaster management

Schweier and Markus (2006) [13] classify the damages focusing on geometrical characteristics of the damaged building, such as volume reduction, inclination changes etc. They have proposed major five types of damages, inclined layers, pancake collapse, debris heaps, overturn collapse and overhanging elements, of damaged levels described above can be recognized using Earth Observation (EO) remote sensing data.

Visual changes such as roof top changes, debris and cluttered environment characterize the earthquake damaged regions. These types of features can be extracted by applying different convolution filters. Below section discusses the proposed deep CNN model for damage detection.

3. DEEP LEARNING MODEL FOR DAMAGE CLASSIFICATION

To maximize the accuracy, robust model design requires flexibility to modify the architectural layers as well as control parameters associated with each layer; hence in this work, entire model is developed from scratch.

Haithi earthquake data (2010), captured by Geoeye1 satellite is used for training the model. Training data is constructed for binary classification to identify whether the region is damaged or not, manual inspection is done to identify the damaged and undamaged images from the entire dataset. Total 280 images (140 each category) of size 128x 128 are used for training the network. Fig. 2 shows the design of proposed Deep CNN model.

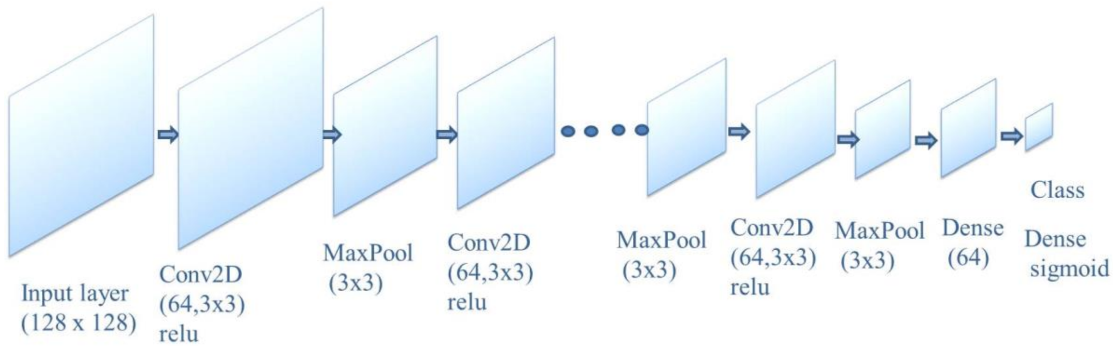

Figure 2. Fine-tuned Deep convolution neural network model designed for disaster damage classification, each layer is labeled below with its associated parameters

Five convolution layers each followed by max pooling layer are added. Convolution is initiated by invoking 64 filters of size 3x3 and max pooling by size 3x3. Dense layer of 64 neurons and the output (class) layer is added; sigmoid activation function is applied on output layer. The loss is measured using binary cross entropy. The depth of the model usually depends on the amount of training samples. For small number of samples, the deeper deep network will perform overfitting [10]. In this model, the depth of the deep learning model is also appropriate and avoids overfitting, also optimizes the computation times. In [5] deep CNN model is developed for damage detection using aerial images that provides damage details with high level of granularity, however satellite images can provide details with coarse level of granularity relative to aerial images; in [5] stereo-views are also considered for training, hence the model designed in this work differs from the model designed in [5] which embeds the transfer learning as well, changes are observed in terms of number of layers (deepness), kernel size, number of filters applied at each convolution layer, number of fully connected layers, dropout ratio, activation function etc.

4. EXPERIMENTAL RESULTS

Sample images from the training set of size 128x128 are shown in figure 3(a) and (b) that represents undamaged region and damaged region respectively. Training data set is created using total 280 images. Google Colab with K80 GPU support is used for implementing the model [7].
All the parameters are set to provide optimal accuracy by minimizing the execution time. 28 samples are used for validation and observed 90% validation accuracy over 200 epochs. The test accuracy is computed for 40 other images (which are not part of training and validation dataset), and observed overall 85% accuracy.

(a)

(b)

Figure 3. Sample training data set used for Deep CNN training that represents a) undamaged regions and b) damaged regions of Haithi earthquake disaster occurred in 2010.

While training the network, significant amount of speedup is observed on GPU platform.
Table 1 shows the time taken by the GPU (K80 with 4996 cores) and only CPU for single epoch and entire training process with 200 epochs for damage classification.

Table 1. Speedup of GPU over CPU for Deep CNN training

Operation	**Only CPU execution time**	**GPU execution time (K80 GPU)**
epoch	3 seconds and 38 millisecond	1 millisecond
Entire training process	11minutes and 46 seconds	33 seconds

5. CONCLUSION

Deep CNN is widely recognized for accurate visual recognition of objects. It is also proven useful in remote sensing domain for geospatial object detection. Remotely sensed VHR satellite images are useful to extract visual features for earthquake damage detection such as debris, broken roof etc. using different convolution filters; considering its characterization capabilities, deep learning model is constructed for disaster data for binary classification.

High performance deep learning classification model is designed and applied on disaster dataset for damage detection. It gives overall 85% test accuracy. Also, significant reduction in execution time is observed when executed on K80 GPU platform, GPU environment is around 20X faster than only CPU environment.

6. REFERENCES

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