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Disaster Damage Assessment of Satellite Images Using Transfer Learning With Fine Tuning

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ABSTRACT
Integration of Emerging technologies offers tremendous potential to build a Rapid Disaster assessment that can accelerate decisions and relief operations. Identifying visible structural damages by various natural calamities and explosions is an essential activity in Rapid Disaster Assessment. Convolution Neural Networks have been shown to outperform traditional methods in a number of recent studies. However, the number of publicly available image datasets for structural disaster damages are limited.
The performance of existing CNN architectures for damage detection in terms of transfer learning with fine-tuning is investigated in this work. Further, a new set of fully-connected layers are placed in VGG16 architecture based on damage-based features extracted from the Dataset. VGG16 is a base of the model which converts each 128x128x3 image to a 4x4x512 block of features. Then features like saturation, contrast, brightness, and sharpness of the images slightly changed to finalize the prediction scores. This model predicts a score on every input image after dividing it into smaller parts, and classification is applied to each of them. Results to input images are scores in the range -1 to 1, informing about the intensity of the damage incurred in the area.
Keywords: Disaster Damage Assessment of Satellite Images, Disaster Damage Assessment Using Transfer Learning, Transfer Learning With Fine Tuning, Disaster assessment

I. INTRODUCTION

Rapid Disaster damage assessment is required for the purpose of immediate rescue and relief operations. Integration of Emerging technologies like AI, IoT, drones, Mobile, data analytics, blockchain offers tremendous potential to build a Rapid Disaster assessment that can accelerate decisions and relief operations. Remotely sensed data can be used to detect building damage in a timely and effective manner. In disaster situations, maps are critical in assisting with response actions. However, the majority of these maps are created by manually extracting data from operational frameworks.

The initial few hours following a disaster are crucial for disaster response. Damaged structures are frequently utilised as a proxy for the impacted population's location. Because of its vast coverage area and data availability, remote sensing is a great technique for locating damaged buildings [1]. Manual catastrophe assessment, on the other hand, is time-consuming, necessitates trained picture analysis, is impractical for wide areas, and is prone to discrepancies owing to human mistake or poor quality control [2]. The use of emerging technology in catastrophe assessment would drastically cut the amount of time it takes to create damage assessment reports. The general goal is to apply image recognition algorithms to satellite photos collected after hurricanes [5, 6].

We collect square-sized images from satellite photography at known building coordinates (accessible from public sources) to produce training, validation, and test datasets. Each square graphic depicts a structure that is either 'Flooded/Damaged' or 'Undamaged.' Then, to identify damaged buildings, a convolution neural network is used. This method, in particular, combines transfer learning with fine-tuning to achieve high accuracy while reducing the amount of processing required to train the classifier

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II. RELATED WORK

The majority of this paper's articles are divided into two main categories: change detection and building damage assessment. In damage assessment, Change detection is used to identify the differences in the image by observing it at different times. To detect change earlier, the researcher used various techniques like algebra-based image differentiating to Change vector analysis, transformation-based techniques like PCA, chi-square, classification-based ANN, and Advanced models like GIS-based [8, 20]. Due to the rapid advancement of technology and deep learning techniques in recent years, segmentation and categorization of data gathered by various sensors and resolutions based approaches have become popular. However, because of the ongoing lack of clarity in their performance under more realistic and operational situations, their use in real-world scenarios has been limited [21]. The method of calculating the amount of damage in the form of scores or percentages is called building damage assessment [22].

Change Detection:

Prior to the advent of deep learning, remote sensing experts conducted substantial study on change detection. Typically, these methods used long-term data sets of geometrically and radiometrically corrected satellite pictures to apply pixel difference-based models [1, 21].

• Radke et al. [13] provided a thorough description of this subset of change detection techniques.

•Deep CNN-based models were recently employed in [20] to categorise the difference photos for change detection.

• In [21], the use of Siamese networks for pixel-wise change detection was investigated.

• F. Nex et al. [8] learned a change detection model from noisy data using an iterative refinement and training approach.

• Change Detection in Multi-Temporal Data has also been done with Recurrent Neural Networks [23].

Building Damage Assessment:

Articles in the literature are based on the segmentation of a building's footprint, and change detection is highly general. Even Nevertheless, few articles have been written about the difficulty of assessing building damage using satellite imagery, and it has gotten only limited attention. For the change detection network, several researchers experimented with simple CNN architectures. The following structure is found to be relevant with the suggested system when using feature differences.

• Yu et al. [23] look into two-stage architecture as a means of detecting damaged structures.

• To recognise building tiles, a Faster RCNN [22] model is used, and a change detection network is used as a binary classifier on pre- and post-disaster building tile pairs.

• For the xBD Dataset, Gupta et al. [17] offer baseline results. For their first stage, they use a U-Net-based algorithm that was originally meant to detect building footprints in Space Net. They also apply a two-stream classification approach for change detection.

III. OBJECTIVES

The Aim and objectives of the system are

- study the effectiveness of current CNN architectures for detecting building damage in terms of transfer learning with fine-tuning[2]
- To extract damage-based features from the Dataset and to place a new set of fully-connected layers in existing architecture based on features.
- To slightly change certain features like saturation, contrast, brightness, and sharpness of the images and check our results.
- To finalize the prediction scores.

IV. EXPERIMENT SETUP

Google Colab is used for training the model on pre-trained weights. Google Colab provides around 25 GB of RAM and a fast and powerful Nvidia Tesla K80 GPU for quick training and operations. But for this system, Model training, Google Colaboratory with 16GB RAM, and Nvidia K80 were used. Quad-core Intel i3 processor or higher, RAM - 8 GB RAM or more expected for trained heavy Dataset and HDD - Varies as per dataset size, but at least 20GB recommended are recommended. Python 3.8 with libraries NumPy/Scikit, Pandas, Matplotlib and Seaborn is used. Model Training is implemented with Tensorflow 2.0/Keras with Google Colaboratory.

V. OVERVIEW OF SYSTEM

Data Collection, Analytic Model, Train Model, and Predictive Model are the four primary components of the design. This system model for damage classification from satellite photos is based on transfer learning with fine-tuning. To accomplish the desired outcomes, transfer learning on pre-trained weights is used. The Image Net Dataset was used to train the VGG16 convolutional neural network model[13]. There are roughly 15 million photos in this dataset, and each image is assigned to over 1000 classes. Over the ImageNet Dataset, VGG16 obtains 92.7 percent top-5 test

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accuracy. However, there are a few disadvantages to adopting VGG16. The most crucial of these is that training it takes a long time. On Nvidia Titan Black GPUs, the real model was trained for weeks.

The network weights for VGG16 are quite crucial, in addition to the time. Convolution layers of 3x3 filters with a stride of 1 are the focus of VGG16. It employs the same padding and max pool layer as stride 2's 2x2 filter. There are 16 layers of weights in VGG16. It has almost 138 million characteristics in total. Because a pertained VGG model has greater computing resources and precision, the suggested model for damage classification is based on a pertained VGG 16 model.

Next, damage-based features are extracted from the Dataset[15]. Here, the fully connected layers of the VGG16 model are removed. Then, a new set of fully-connected layers on top of this network is placed. After that, fine-tuning is applied to these weights to recognize the new object classes as per our requirements. This is quite a very standard technique in the domain of training neural networks and is often recommended, known as fine-tuning. Basically, the model is not trained from scratch but applies transfer learning on pre-trained VGG16 weights. This gives us better results than training the model from scratch and still offers many spectacular options.

Further, binary cross-entropy is used to finalize the prediction scores. Logistic Regression is a known algorithm used to generate output in binary values, mainly 0 and 1. Binary cross entropy will help us for approximation of scores. The Dataset consists of "damage" and "no damage" classes. Here data analysis is applied to find out important parameters for classification. Then the score is generated to differentiate it into five colored classes for a reasonable interpretation of the incurred damage.

Dataset Overview

Satellite photos from Texas after Hurricane Harvey split into two categories (damage and no damage) [3]. There are four folders in the data set: train another, validation another, test another, and test. The training data for each class is contained in the train another folder, which contains 5000 photos. The validation another folder contains 1000 photos of each class's validation data. The imbalanced test data is contained in the test another folder, which contains 8000/1000 photos of damaged/undamaged classes. The balanced test data of 1000 photos for each class is contained in the test folder. The class title is the name of the folder containing the photographs, and all of the images are in JPEG format [3,4]. As a result of the suggested model's resources and precision, it is built on the well-known VGG 16 model for damage categorization.

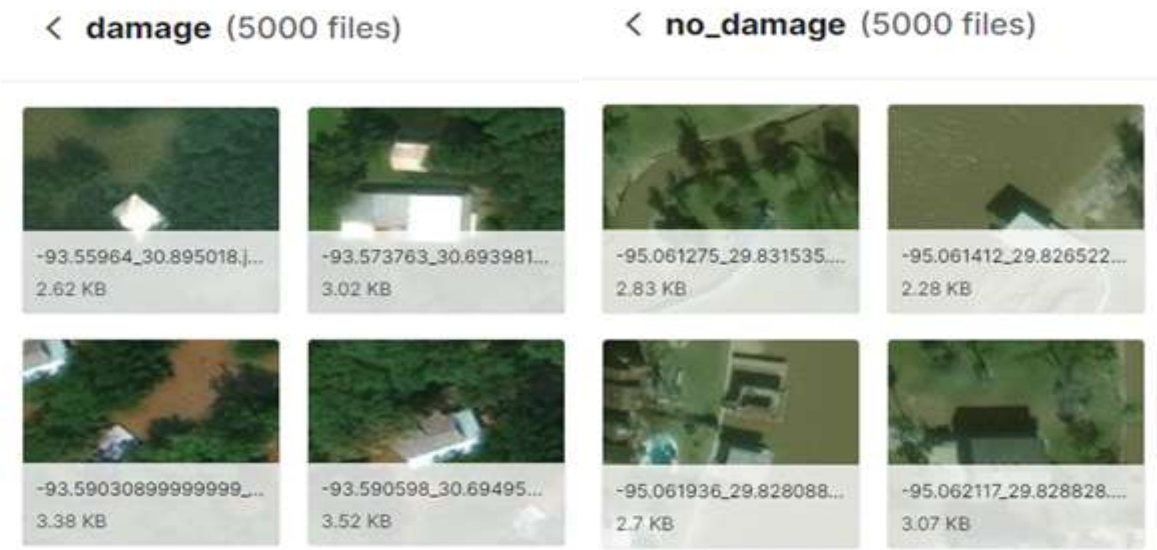

Fig 1: Overview of dataset

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Stratification of Data

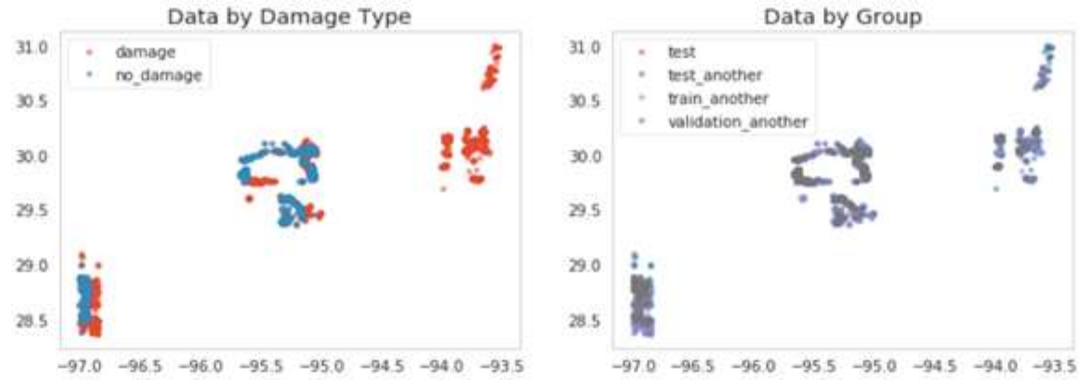

Fig 2 Grouping Data

Image Previews

Fig 4.4 Damage vs No Damage

Fig 4.5 Different Splits

VI. MODEL ARCHITECTURE

Convolution Neural Networks are the foundation of the models used in this system. First analyze the data before training the model to decide the parameters. Pixel count is One of the most important parameters considered for this system because Damaged images tend to have a higher pixel count due to the tension in the plates. Then A data pipeline is generated to test various algorithms on our model, before using convolution neural networks. Various machine learning algorithms were tested before going ahead with binary cross-entropy. Initially, a model is trained with Linear Regression. This gives us very average results. So,

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Decision Trees and Random Forests, and it produce better results. XGBoost is a very powerful classification algorithm. and it gave better results than other methods used before.

Then, instead of using feature extraction, fine-tuning is performed. To fine-tune the model, the next parameter, Model Sensitivity, is chosen. In addition, certain aspects of the images were slightly altered, and the results were double-checked. Saturation, contrast, brightness, and sharpness are some of these characteristics. A colour is represented by three primary colours: red, green, and blue [5], with integer values ranging from 0 to 255. (RGB). Pure red is (255, 0, 0), pure green is (0, 255, 0), and pure blue is (0, 255, 0). (0, 0 , 255) [5].

Saturation is the degree to which a colour is pure. Mid-tones with an imbalance between R, G, and B are the colours with the most potential for high saturation [4]. In a few cases, white stability has a significant impact on saturation because it makes colorings appear more or less natural than before. The most serious flaw with the saturation is that it applies the same saturation power to the entire image at some point[4]. As a result, both the close-to-natural tones and the gentler tones become oversaturated, giving the shot an artificial appearance.

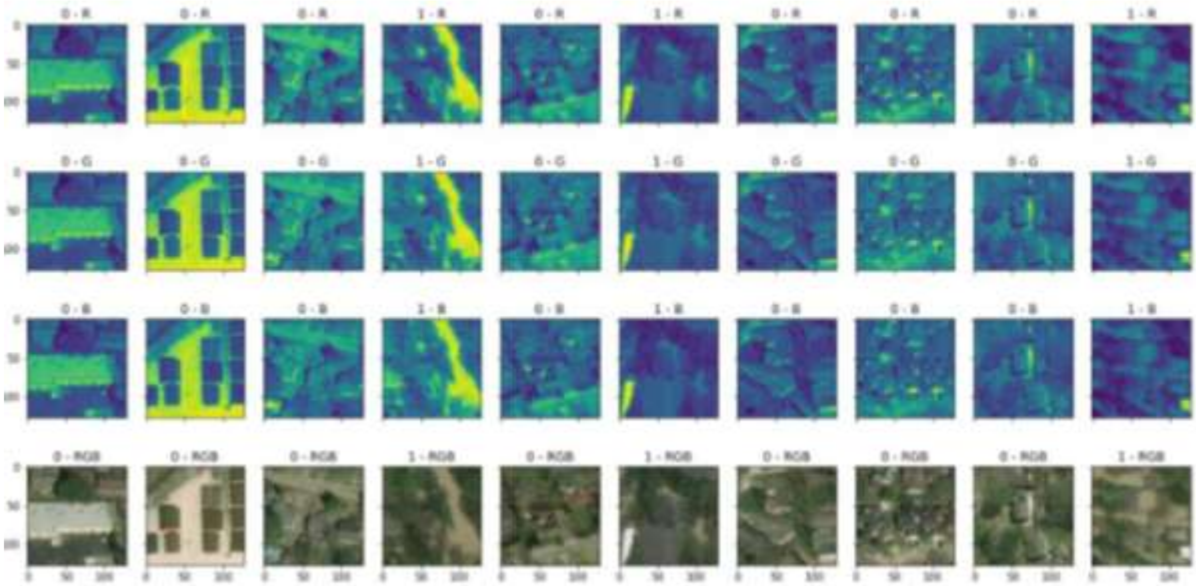
The difference between an image's greatest and least pixel intensity is known as contrast. To put it another way, the image's darkest and brightest pixels have been separated. As a result, raising contrast reduces the distance between the brightest and darkest pixels[4].

After an analog-to-digital converter has digitised the image, brightness is defined as the measure of intensity. The image will lighten as the brightness is increased, whereas the image will darken as the brightness is decreased.

Sharpness: It can be described as the contrast along edges in an image. Increasing sharpness means increasing the contrast only along edges in an image but leaving the smooth spots of the image alone.

Training the model

The satellite images are preprocessed after loading them onto the interface. Further, the images are converted into Tensor flow Tensor format, which is a format used by the libraries to process image data. On the training set images, data augmentation is conducted, including flipping and rotation to randomise the results. The buffer size for shuffling defines how random the Dataset becomes - a buffer size equal to the number of instances will result in a uniform shuffling over the entire Dataset, and a buffer size equal to 1 will result in no shuffling.



Dataset images after preprocessing

Since the data is currently ordered by label, a full shuffle over the entire Dataset is required. The images are converted into shapes of (128, 128, 3), which are also the dimensions images required for VGG16. a new layer of Global Average Pooling 2d is created and pass it on for transfer learning. GlobalAveragePooling2D takes a new approach. The spatial dimensions are average

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pooled until each is one, leaving the other dimensions unaffected. Values are not retained in this case since they are averaged. For example, if the 2nd and 3rd dimensions were spatial, a tensor (samples, 10, 20, 1) would be produced as (samples, 1, 1, 1) [8]. It pools the data by averaging it (GlobalAveragePooling) or finding the maximum value using a parser window that sweeps over the object (GlobalMaxPooling). Padding is essentially required to account for the worst-case scenarios. In essence, it averages all of the numbers along the last axis. We utilised the Adam optimizer with a learning rate of 0.0001 for the optimizer [7]. The Adam optimizer is a well-known gradient descent optimization technique. This optimizer is the most efficient in general because we are dealing with a large number of parameters. We'll utilise Binary Cross-Entropy, also known as Sigmoid Cross-Entropy, for the loss function, which is used to approximate scores. It solved a two-class classification problem. It is independent for each vector component, meaning that the loss calculated for each CNN output vector component is unaffected by the values of other components.

$$CE = -\sum_{i=1}^{C'=2} t_i log(f(s_i)) = -t_1 log(f(s_1)) - (1-t_1) log(1-f(s_1))$$

The formula for Binary Cross-Entropy[]

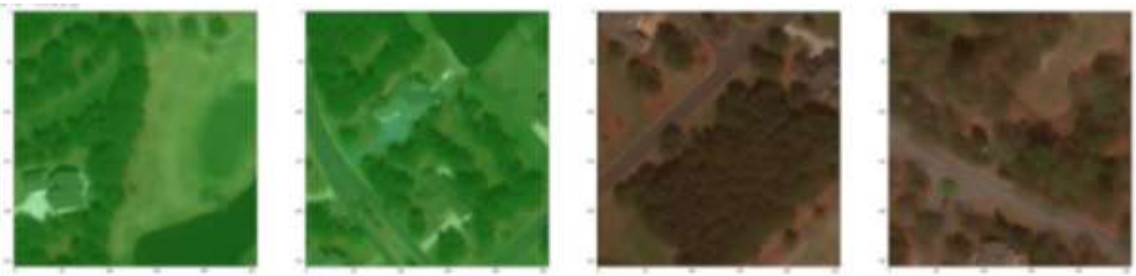
The system considered 20000 images for training, 4000 images for validation, and around 9000 images for the testing phase[3,12]. Initially, the model is trained for 15 epochs. Then, we applied fine-tuning to this model after the training was over. We start fine-tuning from the 15th layer onwards. The learning rate for the Adam optimizer is also divided by 10 [7]. Again, we trained the model with the new parameters for another 25 epochs. Transfer learning helps us to keep snapshots of the model at different epochs, in other words, checkpoints. This helped in case of training stops due to hardware or network issues.

VII. RESULTS

The model achieved 96% accuracy on the validation set with a loss of 0.2719. On the testing dataset, the VGG16 model achieved an accuracy of 96.59% and a loss of 0.2434. The model predicts a score on every input image after dividing it into smaller parts, which describes the amount of damage.

Results to input images are scores in the range -1 to 1, informing about the intensity of the damage incurred in the area. Any score less than or equal to zero, depicts that no damage has occurred to the area. Otherwise, a color mask is assigned as per the score. A darker and bolder mask is assigned to areas with a high damage score.

Range	Color Mask
Equal to 1	Dark Red
Greater than 0.75	Red
Greater than 0.5	Orange
Greater than 0	Yellow
Less than or equal to 0	Green



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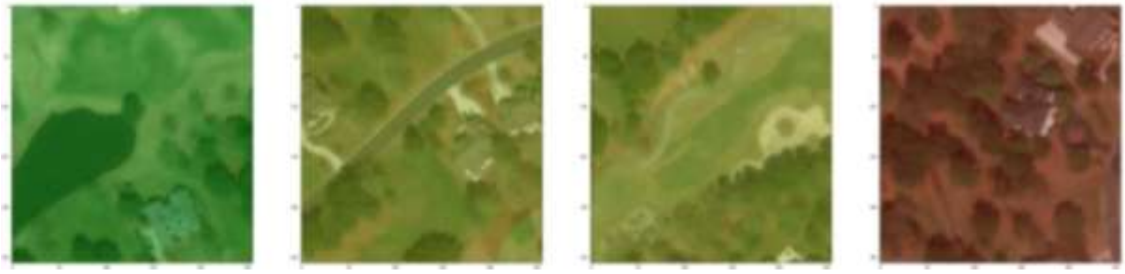

Output masks as predicted by the model.

In the system, prediction is made on the full validation and test sets with associated Dataset, the best performance achieved using Convolution Neural Network, Data Augmentation, 50% Dropout in the fully connected layer and Adam optimizer and got Validation Accuracy- 98.06% and Test Accuracy (Balanced)- 97.29%.

VIII. CONCLUSION

The performance of current CNN architectures for constructing damage detection in terms of transfer learning with fine-tuning was explored in this research. In addition, based on damage-based characteristics derived from the Dataset, a new set of fully-connected layers is added to the VGG16 architecture. Then, to finish the prediction scores, attributes including saturation, contrast, brightness, and sharpness of the photos were significantly altered. After breaking each input image into smaller sections, this model predicts a score that indicates the extent of damage. VGG 16, which detects obvious structural damage, is put to the test to discover what deep learning networks can do right now. Its implementation in real-world operational scenarios following natural disasters is described. For the same, a dataset featuring satellite images of hurricane damage in Texas was explored. On the validation set, the model had 96 percent accuracy with a loss of 0.2719, while on the testing set, the model had 96.59 percent accuracy with a loss of 0.2434. Satellite photos are used as input to the system. These images are divided into smaller sections, and each is classified. The results of the supplied images are scores ranging from -1 to 1, indicating the severity of the damage in the area. There is no damage to the region if the score is less than or equal to zero. Otherwise, the score determines which colour mask is used. Areas with a high damage score are given a darker and bolder mask.

REFERENCES

[1] R. Foulser-Piggott, R. Spence, K. Saito, D. Brown, and R. Eguchi, “The use of remote sensing for post-earthquake damage assessment: lessonsfrom recent events, and future prospects, Proceedings of the fifthteenth world conference on earthquake engineering, lisbon, portugal, 2012.

[2] C. Axel and J. A. van Aardt, “Building damage assessment using airborne lidar,” Journal of Applied Remote Sensing, vol. 11, no. 4, p.046024, 2017.

[3] Kaggle Dataset: https://www.kaggle.com/kmader/satellite-images-of-hurricane-damage, access date: 10/11/2020

[4] L. Duffy. Fighting natural disasters with satellite imagery[Online]. Available: https://www.pobonline.com/articles/101492-fighting-natural-disasters-with-satellite-imagery

[5] J. Doshi, D. Garcia, C. Massey, P. Llueca, N. Borensztein, M. Baird, M. Cook, and D. Raj, “Firenet: Real-time segmentation of fire perimeter from aerial video,” Artificial Intelligence for Humanitarian Assistance and Disaster Response Workshop, NeurIPS, 2019 [Online]. Available: https://arxiv.org/abs/1910.06407

[6] G. Mateo-Garcia, S. Oprea, L. Smith, J. Veitch-Michaelis, A. G. Baydin, and D. Backes, “Flood detection on low cost orbital hardware,” Artificial Intelligence for Humanitarian Assistance and Disaster Response Workshop, NeurIPS, 2019. [Online]. Available: https://arxiv.org/abs/1910.03019

[7] A. J. Cooner, Y. Shao, and J. B. Campbell, "Detection of urban damage using remote sensing and machine learning algorithms: Revisiting the 2010 Haiti earthquake," Remote Sensing, vol. 8, no. 10, p. 868, 2016.

[8] F. Nex, D. Duarte, F. G. Tonolo, and N. Kerle, “Structural building damage detection with deep learning: Assessment of a state-of-the-art CNN in operational conditions,” Remote sensing, vol. 11, no. 23, p. 2765, 2019.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 1565-1572 www.ijaem.net ISSN: 2395-5252

[9] Y. Li, W. Hu, H. Dong, and X. Zhang, "Building damage detection from post-event aerial imagery using single shot multibox detector," Applied Sciences, vol. 9, no. 6, p. 1128, 2019.

[10] J. Z. Xu, W. Lu, Z. Li, P. Khaitan, and V. Zaytseva, "Building damage detection in satellite imagery using convolutional neural networks," Artificial Intelligence for Humanitarian Assistance and Disaster Response Workshop, NeurIPS, 2019. [Online]. Available: https://arxiv.org/abs/1910.06444

[11] R. Hamaguchi and S. Hikosaka, "Building detection from satellite imagery using ensemble of size-specific detectors," in 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). IEEE, 2018, pp. 223–2234.

[12] S. Golovanov, R. Kurbanov, A. Artamonov, A. Davydov, and S. Nikolenko, "Building detection from satellite imagery using a composite loss function," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2018, pp. 229–232.

[13] R. J. Radke, S. Andra, O. Al-Kofahi, and B. Roysam, "Image change detection algorithms: a systematic survey," IEEE transactions on image processing, vol. 14, no. 3, pp. 294–307, 2005.

[14] R. Deng, C. Shen, S. Liu, H. Wang, and X. Liu, "Learning to predict crisp boundaries," in Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 562–578.

[15] Weber, Ethan and Hassan Kan'e. "Building Disaster Damage Assessment in Satellite Imagery with Multi-Temporal Fusion." ArXiv, vol. abs/2004.05525, April 2020

[16] Hanxiang Hao, Sriram Baireddy, Emily R. Bartusiak, Latisha Konzy Kevin LaTourettey Michael Gribbonsy Moses Chany, Mary L. Comer, Edward J. Delp, , "An Attention-Based System for Damage Assessment Using Satellite Imagery", Video and Image Processing Lab (VIPER), Purdue University, West Lafayette, Indiana USA, Lockheed Martin Space, Sunnyvale, California, USA.

[17] Rohit Gupta and Mubarak Shah, "RescueNet: Joint Building Segmentation and Damage Assessment from Satellite Imagery", , Center for Research in Computer Vision, University of Central Florida, Orlando, Florida 32816.

[18] Emerging Technology Trends that can Transform Disaster Management in India - IndBiz | Economic Diplomacy Division | IndBiz | Economic Diplomacy Division

[19] Quoc Dung Cao, Youngjun Choe, December 13, 2018, "Detecting Damaged Buildings on Post-Hurricane Satellite Imagery Based on Customized Convolutional Neural Networks", IEEE Dataport, doi: https://dx.doi.org/10.21227/sdad-1e56.

[20] Wenzhong Shi , Min Zhang, Rui Zhang, Shanxiong Chen , Zhao Zhan, "Change Detection Based on Artificial Intelligence: State-of-the-Art and Challenges", Journal of Remote Sensing, ,April 2020.

[21] Le Yang, Yiming Chen , Shiji Song, Fan Li ,Gao Huang," Deep Siamese Networks Based Change Detection with Remote Sensing Images", Journal of Remote Sensing, 13, 3394. https://doi.org/10.3390/rs13173394, ,2021

[22] Maria Papadomanolaki, Sagar Verma, Maria Vakalopoulou, Konstantinos Karantzalos, "Detecting Urban Changes with Recurrent Neural Networks from Multitemporal Sentinel-2 Data", IEEE International Geoscience and Remote Sensing Symposium, , 2019

[23] Yu Shen, Sijie Zhu, Taojiannan Yang, Chen Chen, Delu Pan, Jianyu Chen, Liang Xiao, Qian Du, "BDANet: Multiscale Convolutional Neural Network with Cross-directional Attention for Building Damage Assessment from Satellite Images", Journal of Latex Class Files, May 2021