Towards Robust Building Damage Detection: Leveraging Augmentation and Domain Adaptation

1st Bharath Chandra Reddy Parupati
dept. School of Computing
Wichita State University
Wichita, USA
bxparupati@shockers.wichita.edu

2nd Dr.Shruti Kshirsagar
dept. School of Computing
Wichita State University
Wichita, USA
shruti.kshirsagar@wichita.edu

3rd Dr.Atri Dutta
dept. Aerospace Engineering
Wichita State University
Wichita, USA
atri.dutta@wichita.edu

***Abstract*—The growing frequency and intensity of natural disasters demand efficient and accurate building damage assessment for effective disaster response. This study identifies critical limitations in existing deep learning models to generalize across minor and major damage classes due to model limitations in identifying the edges and corners of the buildings from satellite images, which are crucial in extracting structural information. To address these challenges, we propose a fusion-based data augmentation technique that integrates edge detection, contrast enhancement, and unsharp masking channels with RGB channels of the input image to improve the detection of building edges and corners. Additionally, domain adaptation methods, including fine-tuning and Deep CORAL, are employed to evaluate the generalizability of fusion-based augmentation in domain shifts between source (xBD) and target domain datasets (Ida-BD). Experimental results reveal that fusion-based augmentation significantly enhances damage classification accuracy and improves model generalization to out-of-domain datasets by enhancing structural feature detection.**

***Index Terms*—Building Damage Detection (BDD), Deep learning (DL), Data Augmentation, Domain Adaptation**

I. Introduction

The frequency of natural disasters, such as wildfires, hurricanes, floods, and earthquakes, has been steadily increasing. Climate change is a significant contributor, intensifying the severity of certain hazards, including extreme weather events [6]. These disasters have devastating consequences, not only disrupting lives but also causing substantial economic losses [19]. Accurate building damage assessments are essential for effective humanitarian responses, as they provide critical data to help decision-makers prioritize emergency measures and allocate resources efficiently to the areas most in need. Achieving rapid assessments—ideally within hours to days—is vital for coordinating relief activities and supporting affected regions [15].

Traditional assessment methods, which often rely on manual inspections or basic image analysis, are labor-intensive, time-consuming, and prone to human error, particularly in large-scale disasters [7]. Such limitations hinder the efficiency of rapid response efforts [1].

To address these challenges, researchers have increasingly turned to deep learning (DL) models and satellite imagery to streamline building damage assessments [7]. DL models can process large volumes of data and automatically identify damaged structures, accelerating disaster response efforts. Advanced models, such as Convolutional Neural Networks (CNNs), ResNet, and transformer-based architectures, offer highly automated and detailed analyses of satellite and aerial imagery (e.g., [5], [8], [9]).

Building damage often impacts the geometrical properties of structures, such as edges and corners [1]. Detecting these features enables models to localize and analyze damaged regions, aiding in distinguishing different levels of damage (e.g., no damage, minor damage, major damage, or destroyed). Data augmentation techniques, which increase the diversity of training data without adding complexity, are widely recognized for improving the robustness of DL models against noise and variations in size, rotation, and color [10]. These techniques also help reduce overfitting, leading to significant performance improvements in DL models.

Motivation: Despite advancements, current benchmarks, such as the xBD dataset, fail to accurately capture the edges and corners of buildings in satellite images, which are crucial for localizing structures and classifying damage. Notably, the top-3 solutions from the xView2 competition exhibit limitations in defining building edges, making it particularly challenging to classify buildings with minor and major damage. Addressing these shortcomings is critical for improving model performance in real-world disaster scenarios.

II. Related Work

In this section, we review state-of-the-art methods for Building Damage Detection, explore existing literature on data augmentation and domain adaptation techniques, and outline our contributions to advancing this field.

Building Damage Detection Recent advancements in damage detection models, since the launch of the xBD dataset and xView2 competition [7], have focused on improving generalization and performance across diverse disaster scenarios and geographic regions. Kaur et al. [5] proposed DAHiTrA, a transformer-based model that incorporates hierarchical spatial features to fuse pre- and post-disaster images into a unified feature space, surpassing traditional CNN architectures. These technologies collectively enable robust and flexible building

Identify applicable funding agency here. If none, delete this.

damage detection models, crucial for effective disaster prediction and management.For our research, we used the top-3 winning solution codes and their performance metrics (F1-scores) as baselines. These models have been deployed in real-world building damage assessments in regions like Australia and California [19].

Data Augmentation Data augmentation plays a crucial role in advancing deep learning (DL) models for building damage detection by addressing data constraints and enhancing model robustness. Standard augmentation techniques, such as flips and rotations, enrich the training dataset by introducing variations [10]. Fusion algorithms further enhance data diversity by incorporating additional spectral features, thereby adding depth to satellite imagery [11].Albumentations, a versatile library, facilitates efficient task-specific augmentations, optimizing model performance [12]. To mitigate the bias inherent in the xBD dataset, D. Melamed et al. [15] introduced object-level metrics and artificial isolated damage models to address clustering issues. Their use of Poisson blending to create synthetic isolated damage scenarios significantly improved model accuracy. Collectively, these augmentation methods bolster model robustness and adaptability for real-world damage detection applications.

Domain Adaptation To ensure that building damage detection models perform reliably across diverse and unseen disaster scenarios, domain adaptation techniques are essential. Approaches like fine-tuning, CycleGAN, and domain adversarial training address domain gaps between source and target datasets. Fine-tuning adapts models with limited labeled data [5], CycleGAN modifies image styles to align with specific disaster types [16], and domain adversarial training facilitates domain-invariant feature learning for robust cross-domain generalization [16]. Jakub et al. demonstrated the effectiveness of unsupervised domain adaptation (UDA) in natural hazard classification. By leveraging pre-trained U-Net architectures for building localization, their approach enabled general hazard segmentation, allowing zero-shot adaptation to novel hazards without the need for target-specific fine-tuning [16]. Furthermore, UniDA and source-free adaptation techniques enhance robustness by enabling models to handle unknown label sets and generate synthetic data when source data is unavailable [18]. These methods are critical for ensuring robust performance across various disaster types and geographic regions.

The existing literature reveals that models trained on xBD data struggle to generalize effectively across multiple damage classes, particularly for minor and major damage categories. Furthermore, as far as we know, there is no augmentation method specifically designed for building damage detection. To address this gap, we propose a simple fusion-based augmentation technique to enhance the model's ability to detect building edges and improve both localization and damage classification performance. Additionally, we demonstrate how this augmentation strategy, combined with domain adaptation techniques, improves model performance on out-of-domain datasets.

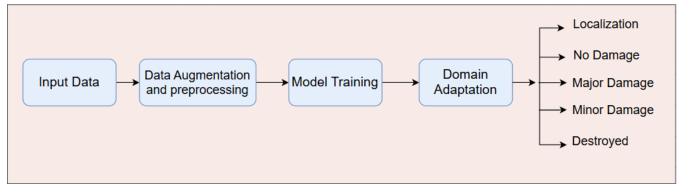


Fig. 1: Block Diagram of Implementing Proposed Methodology

III. METHODS & MATERIALS

In this sections, we described our proposed method based on data augmentation and domain adaptation methods.

1) Proposed Method: As described in fig 1 , we utilized data augmentation and domain adaptation method.

A. Data augmentation

1) Fusion Augmentation for Building Damage Detection: Fusion-based data augmentation, as described in the original work [11], is a data augmentation technique that fuse auxiliary channels(or custom bands) with each training instance and this can be seen as spectral-spatial fusion process. Unlike instance-based augmentation [2] - [4], which primarily alters the original image through techniques such as rotation, cropping, masking, flipping, or noise addition, fusion-based augmentation enriches the data by adding more spectral or spatial information to the input images. This technique increases the dimensionality of the data rather than the number of training instances. Key Methods of Fusion-Based Augmentation are:

Edge Detection:Edges are among the most important features associated with images. We know the underlying structure of an image through its edges. So, in case of building damage detection using satellite images where buildings are typically confined to a small number of pixels and we might have those pixels associated with buildings and other structures close to each other, which are very hard to identify by kernels in initial layers of convolutional networks. So, finding these edge details and defining corners will be crucial in identifying the damaged buildings. This augmentation process involves extracting edge features (lines, boundaries) from images and fusing them with the standard RGB bands [11]. The study used gradient-based edge detection to create these features, which are particularly beneficial for improving the model's focus on structural aspects like building outlines and damage edges. In our experiments to find the best gradient-based edge detection method suitable to our dataset, we found Canny Edge Detection derived the best results because it uses not only Sobel Edge Detection but also Non-Maximum Suppression and Hysteresis Thresholding [20].

The core idea is to find the maximum and minimum in the first derivative of the image, where pixels with a high gradient are considered edges. This method highlights areas where there is a significant change in intensity, making it easier to identify the boundaries of objects within the image. By highlighting these features early in the network, the model better captures critical structural information. This provides more flexibility in how edges are identified and connected in the final stages of the algorithm.

Contrast Enhancement: This technique enhances image contrast, making objects stand out more clearly against the background. The enhanced contrast is combined with the input image to expose subtle details that may otherwise be missed by the model [11]. Histogram equalization, a common contrast enhancement method, was used in this study. Although contrast enhancement is used as one of the augmentation technique in baseline state-of-the-models[[2]-[4], we are fusing this channel with edge detection to help in representing more details in the image. The combination of edge detection channel and contrast enhancement channel gave best results in the original work for satellite super resolution [11].

Unsharp Masking: Unsharp masking is a simple technique to enhance image details by creating a mask through the subtraction of a blurred version of the original image from itself. If A represents the original image and B the blurred version, the mask is calculated as mask $= B - A$. This mask is then added back to the original image, resulting in a sharpened output. Incorporating this channel into training is presumed to emphasize deblurring features, although its contribution is less significant than gradient edge features [11]. This process helps the model to better capture fine details such as texture, which helps in minor damage cases.

In order to evaluate the fusion-based augmentation on xBD dataset, A grayscale scene was generated to derive the unsharp mask, contrast-enhanced, and gradient edge bands, along with RGB channels. These selected channels were combined into a stacked representation, followed by cropping patches of size as used in the top-3 winning solution. This method was added in the image preprocessing stage in the ML pipleine followed by model training and evaluation.

(a) Post Disaster Image

(b) Post disaster building localization of xView-2 first place winning solution [2]

(c) Post disaster building localization after applying fusion-based augmentation

Fig. 2: The figure shows the effectiveness of fusion-based augmentation on post-disaster images using xView-2 winning solution. In subfigure (c), the improvements are marked in red circular highlights.

The Figure 2 shows the comparison of localization(which predicts building presence) output for top-1 winning solution of xView-2 competition. Figure 2a is the post disaster image on which model predicts the building presence, Figure 2b is the output before applying proposed augmentation. This output missed predicting the presence of all buildings in input satellite image. Figure 2c shows output of the localization after applying proposed method. This identifies edges and corners of the buildings better than the previous version.

B. Domain Adaptation

Data augmentation techniques that work well in trained domain may not work well in a different domain due to disparate distributions and properties of data. Domain adaptation is the practice of adapting models developed in one domain to excel in another, yet related domain. Through domain adaptation, testing if proposed data augmentation techniques are still efficient across different domains, which means it allows for greater application. If a data augmentation approach improves performance even after domain adaptation, then that technique is resilient to changing data characteristics [21] (an important property in areas such as remote sensing where data can be highly heterogeneous).

This paper demonstrates that the proposed augmentation technique is capable of generalizing other datasets using a simple transfer learning approach and an unsupervised domain adaptation approach. Satellite images are so heterogeneous (e.g.,locational-related, landscape and weather-related) that machine learning models are difficult to generalize. For example, the model trained from the xBD data typically does not perform well with other data. The target domain in this experiment is the Ida-BD dataset, which shows significant domain drift from xBD. To combat this and test the generalizability of the proposed augmentation method, we used two methods discrepancy-based fine-tuning using a low amount of labeled target data and Deep CORAL, an unsupervised domain adaptation method that aligns domain features without labeled target data.

Fine Tuning: This is a simple method of transfer learning. Fine-tuning is performed using a pretrained model (in our case, top-1 winning solution). During fine-tuning the weights of the pretrained model are adjusted using the target domina data, this process enables the model to adapt to new domain while retaining its previous knowledge [5]. If labeled data is available for the target region (like annotated images from a recent hurricane), the model initially trained on a broader dataset (e.g., xBD) can be fine-tuned using these labeled samples. This approach allows the model to retain generalizable features from the source disaster while learning characteristics specific to the new disaster. We used 30% of the Ida-BD dataset for fine-tuning.

CORAL(CORrelation ALignment) Domain Adaptation [14]: is an unsupervised domain adaption approach. In real time, finding labeled dataset with proper annotations for building damage is not so feasible. So the model should be able to generalize to new disaster even where no labeled data is available. CORAL can handle such domain changes by matching feature distributions between source and target domains without any need for labeled data [14].

CORAL reduces the gap between the source and target domain covariance matrices by adding a CORAL loss term to the training goal [14]. This loss term computes the Frobenius norm(a matrix distance function) of the difference between the covariance matrices of the source and target features in the domain.

$$L_{\text{CORAL}} = \frac{1}{4d^2}\|C_S - C_T\|_F^2 \qquad ([14])$$

where C_s and C_t represent the covariance matrices of the source and target features, respectively, and $\|\cdot\|_F$ denotes the Frobenius norm.

Combining Losses: Combine the CORAL loss with the primary task loss (e.g., classification loss) to form the total loss function:

$$L = L_{\text{class}} + \sum_{i=1}^{t} \lambda_i L_{\text{Coral}} \qquad ([14])$$

- L_class is the standard classification loss used to train the classifier on the source data.
- L_coral is the CORAL loss term that reduces domain shift by aligning the covariance between source and target features.
- t denotes the number of CORAL loss layers in a deep network.
- λ_i is a weighting factor for the CORAL loss at each layer. Test with different values based on the performance on the validation set.

IV. Experimental Setup

A. Dataset

xBD dataset: Before the introduction of xBD, the availability of datasets for building damage detection using satellite imagery was limited in scope and diversity. Most datasets focused on single disaster types, such as floods, earthquakes, or fires, and lacked standardized damage assessment criteria. The xBD provides a vast collection of satellite images, spanning 45,362 km^{2}across 19 natural disasters worldwide [1]. A notable challenge with the xBD dataset is its class imbalance. Out of the 850,736 building annotations, the ”no damage” class is heavily overrepresented with 313,033 instances, while classes like ”minor damage” (36,860), ”major damage” (29,904), and ”destroyed” (31,560) are significantly fewer [1]. This imbalance can skew the model towards predicting ”no damage,” requiring techniques like data augmentation to address the bias. The model is trained using the Train and Tier 3 sets provided by the competition and evaluated on the given Test set [1].

Ida-BD dataset: Kaur et al., [5] created a new dataset of temporal images specially designed for building damage classification similar to xBD. Ida-BD is a dataset with 87 pre and post-disaster satellite imagery pairs with a very high resolution (0.5m/pixel) from Hurricane Ida 2021 in Louisiana, USA. Ida-BD dataset can serve as a benchmark dataset for domain adaptation because of its variance from larger datasets like xBD.

B. Figure of Merits & Testing setup

C. Benchmark systems

V. Experimental Results and Discussion

A. Effect of data augmentation with benchmark systems

B. Effect of domain adaptation and data augmentation with benchmark system on unseen dataset

This chapter consists of the experiments conducted, the results obtained, and a detailed analysis of the results. Initially, the top-3 winning solutions were run on a local machine and tested using the competition-provided test set we call it as In-domain dataset (ID). The results in Table I display the performance of these winning solutions on the competition's test split before and after applying proposed augmentation. On an average, the fusion-based augmented model performance has improved by 5-7% in Minor and Major damage classes, 2.5% improvement in localization, and a modest 1% improvement in no-damage class. This demonstrates that fusion-based augmentation in combination with geometric augmentations is effective in improving building damage classification.

TABLE I: Performance comparison of top-3 winning solutions on competition provided test set before and after applying proposed augmentation

Class	1st	1st+Aug	2nd	2nd+Aug	3rd	3rd+Aug
Localization	0.8621	0.8945	0.85318	0.8926	0.8465	0.88272
No Damage	0.9147	0.9391	0.9018	0.9364	0.9071	0.92952
Minor Damage	0.6385	0.6958	0.6181	0.68317	0.6173	0.66709
Major Damage	0.7819	0.8159	0.7702	0.80629	0.7651	0.80125
Destroyed	0.8542	0.8825	0.8486	0.87401	0.8462	0.87461

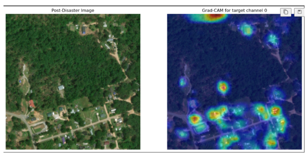
Figure 3 is the GRAD CAM output of the top-1 winning solution classification prediction on the input post-disaster satellite images. Fig 3a and 3c is the output of model which uses geometrical augmentations and Fig 3b and 3dis the output after applying fusion based augmentation. The visual analysis of outputs explains that fusion based augmentation along with geometrical augmentation is more effective in identifying and classification of building damage by helping the model to detect the edges and corners of buildings more precisely.

C. Analyzing Generalizability of The Fusion Based Augmentation

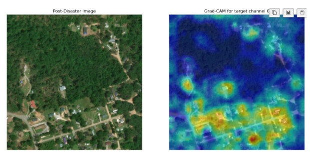
The Purpose of this section is to demonstrate how the fusion based augmentation is effective in out-of-domain datasets, we are using Ida-BD dataset for our experiments. Please not that the methods used in this experiments are not necessarily better than rest of the domain adaptation methods. The authors used the following methods to evaluate the data augmentation generalization performance, this work experiments with 6 training settings by using top-1 winning solution [2] as the baseline model for reference on performance. For all the experiments the model is pre-trained on xBD dataset.F1 Score

TABLE II: Results of Domain Adaptation

Methods	Localization	No-Damage	Minor-Damage	Major-Damage	Destroyed
Pretrained model	0.8056	0.6673	0.2107	0.1538	0.041
Pretrained model+Augmentation	0.8149	0.6631	0.2348	0.1726	0.052
Pretrained model+Fine-Tuning	0.8419	0.6724	0.2923	0.1837	0.0954
Pretrained model+Fine-Tuning+Augmentation	0.8485	0.6961	0.3147	0.1920	0.117
Pretrained model+CORAL DA	0.8146	0.6581	0.2753	0.1346	0.059
Pretrained model+CORAL DA+Augmentation	0.8215	0.6641	0.3016	0.1452	0.0631

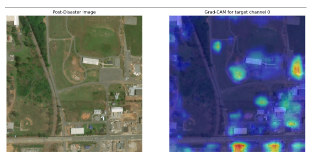


(a) Example-1 of Top-1 Winning solution output with geometrical augmentation



(b) Top-1 Winning solution output after applying proposed augmentation

(c) Example-2 of Top-1 winning solution output with geometrical augmentation



(d) Top-1 Winning solution output after applying augmentation

Fig. 3: Comparison of model predictions before and after applying proposed augmentation(The input images are considered from different disasters)

is used as the performance metric in all the experiments. The following are the experiment settings used in this work.

- Top-1 winning solution trained on xBD and tested on Ida-BD dataset
- Top-1 winning solution trained on xBD by adding fusion based augmentation
- Top-1 winning solution trained on xBD and fine-tuned on Ida-BD dataset
- Top-1 winning solution trained on xBD by adding fusion based augmentation and Fine-tuned on Ida-BD dataset
- Top-1 winning solution trained on xBD and applied CORAL DA(considering no labled data is available)
- Top-1 winning solution trained on xBD by adding fusion based augmentation and applied CORAL DA

Finally, as shown in Table II in all the experiments where fusion based augmentation is used showed an effective improvement in the classification performance of the model. This shows that deriving unique channels with different properties and fusing them with RGB satellite image is effective in identifying building edges and corners more precisely which helped the model to detect buildings more accurately and classify into their damage class.

VI. Conclusion

We demonstrated that top-3 xView2 solutions cannot properly identify the edges and corners of the buildings from the satellite image which is one of the reason for not generalizing equally well on all the damage classes and consequently show poor performance on minor and major damage classes. We propose a fusion augmentation strategy to improve the generalization ability of the existing models by evaluating it on the top-3 winning solutions. Furthermore, we demonstrate how fusion augmentation is effective during domain adaptation of the model to unseen location.

Future work will expand on how fusion augmentation helps to reduce the bias of the model to certain terrains and architectural properties. We hope this work continues to drive good progress in automated building damage detection, highlighting the necessity for models to be more effective in identifying the structural properties of buildings in different geographical regions.

Acknowledgment

should confirm with DR. Atri regarding this section

References

[1] Gupta, Ritwik, et al. "Creating xBD: A dataset for assessing building damage from satellite imagery." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops. 2019.

[2] V. Durnov, "xview2 first place." https://github.com/DIUx-xView/xView2 first place/tree/master, 2020.

[3] S. Seferbekov, "xview2 second place." https://github.com/DIUx-xView/xView2 second place/tree/master, 2020.

[4] E. Khvedchenya, "xview2 third place," https://github.com/DIUx-xView/xView2 third place, 2020.

[5] Kaur, Navjot, et al. "Large-scale building damage assessment using a novel hierarchical transformer architecture on satellite images." Computer-Aided Civil and Infrastructure Engineering 38.15 (2023): 2072-2091.

[6] Climate.NASA.GOV, "What are the effects of climate change on extreme weather. https://science.nasa.gov/climate-change/extreme-weather/

[7] xView2 Access Building Damage, "Computer vision for building damage assessment." https://xview2.org/.

[8] Jakubik, Johannes, et al. "Toward foundation models for earth monitoring: Generalizable deep learning models for natural hazard segmentation." IGARSS 2023-2023 IEEE International Geoscience and Remote Sensing Symposium. IEEE, 2023.

[9] Duarte, Diogo, et al. "Satellite image classification of building damages using airborne and satellite image samples in a deep learning approach." ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences 4 (2018): 89-96.

[10] Adedeji, Oluwadara, et al. "Image augmentation for satellite images." arXiv preprint arXiv:2207.14580 (2022).

[11] Ghaffar, M. A. A., et al. "Data augmentation approaches for satellite image super-resolution." ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences 4 (2019): 47-54.

[12] Buslaev, Alexander, et al. ”Albumentations: fast and flexible image augmentations.” Information 11.2 (2020): 125.

[13] O. S. C. Vision, “Canny edge detection,” *OpenCV Documentation*, Available: https://docs.opencv.org/4.x/da/d22/tutorialpycanny.html?refblog.robo.flow.com.

[14] Sun, Baochen, and Kate Saenko. ”Deep coral: Correlation alignment for deep domain adaptation.” Computer Vision–ECCV 2016 Workshops: Amsterdam, The Netherlands, October 8-10 and 15-16, 2016, Proceedings, Part III 14. Springer International Publishing, 2016.

[15] Melamed, Dennis, et al. ”Uncovering Bias in Building Damage Assessment from Satellite Imagery.” IGARSS 2024-2024 IEEE International Geoscience and Remote Sensing Symposium. IEEE, 2024.

[16] Hu, Yijiang, and Hong Tang. ”On the generalization ability of a global model for rapid building mapping from heterogeneous satellite images of multiple natural disaster scenarios.” Remote Sensing 13.5 (2021): 984.

[17] Jakubik, Johannes, et al. ”Toward foundation models for earth monitoring: Generalizable deep learning models for natural hazard segmentation.” IGARSS 2023-2023 IEEE International Geoscience and Remote Sensing Symposium. IEEE, 2023.

[18] Xu, Qingsong, et al. ”Universal domain adaptation for remote sensing image scene classification.” IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-15.

[19] NASA, ”Applied Science” https://appliedsciences.nasa.gov/our-impact/news/fighting-fires-together-xview-2-prize-challenge-helps-automate-damage-assessments

[20] OpenCV,”Canny Edge Detection”,https://docs.opencv.org/3.4/da/d22/tutorial py canny.html

[21] Li, Pan, et al. ”A simple feature augmentation for domain generalization.” Proceedings of the IEEE/CVF International Conference on Computer Vision. 2021.