Towards Robust Building Damage Detection: Leveraging Augmentation and Domain Adaptation

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***Abstract*—The increasing frequency of natural disasters necessitates efficient building damage detection for effective disaster response. This study addresses limitations in deep learning models, particularly their inability to classify minor as well as major damage classes due to inadequate detection of structural features like edges and corners in satellite images. To overcome these challenges, we propose the utilization of a fusion-based data augmentation technique that combines edge detection, contrast enhancement, and unsharp masking to enhance structural feature detection. We further evaluate the generalizability of this approach using domain adaptation techniques, including supervised fine-tuning and unsupervised Deep CORAL to address domain shifts between source (xBD) and target (Ida-BD) datasets. Experimental results demonstrate that the proposed augmentation improves damage classification accuracy by 5–7% in minor and major damage classes and enhances localization accuracy by 2.5%. Additionally, the integration of domain adaptation techniques validates the robustness in handling out-of-domain datasets. By improving structural feature detection and mitigating domain discrepancies, the proposed methodology enhances performance and adaptability of deep learning models for disaster response. This study demonstrates the potential of fusion-based augmentation and domain adaptation to enable reliable and efficient building damage detection in diverse disaster scenarios.**

***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 [1]. These disasters do not only lead to devastating consequences but also disrupt lives causing substantial economic losses [2]. In the aftermath of a natural hazard, assessment of structural damage in buildings is essential for effective humanitarian responses, as they provide critical data to help decision makers. Achieving rapid assessments, ideally within hours to days, is vital for coordinating relief activities and for supporting affected regions [3].

Traditional assessment methods [4] that often rely on manual inspections or basic image analysis are labor-intensive, time-consuming, and prone to human error, particularly in large-scale disasters [5]. Such limitations hinder the efficiency of rapid response efforts [6].

To address these challenges, researchers have increasingly turned to deep learning (DL) models and satellite imagery to streamline building damage assessments [5]. Satellites are strategically positioned to obtain information about a large number of buildings in a given geographical area, irrespective of difficulties in terrestrial accessibility caused by the disaster. 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., [7], [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 [6], 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 three winning solutions from the xView2 competition [5] exhibit limitations in determining 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. In this work, we aim to fill the gap by utilizing effective data augmentation and domain adaptation methods.

The remainder of this paper is structured as follows: Section II provides related works. Section III explains the methods & materials, whereas the experimental setup was discussed in Section IV. Next, Section V presents experimental results and a discussion, and finally, section VI provides conclusion and future work.

This work was supported by a REI grant (FY2023-090-M2) from Kansas NSF EPSCOR program.

II. Related Work

In this section, we review state-of-the-art methods for building damage detection and outline our contributions to advancing this field.

Building Damage Detection Recent advancements in damage detection models, such as top solutions of the xView2 competition [5], have focused on improving generalization and performance across diverse disaster scenarios and geographic regions. Kaur et al. [7] 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.

Data Augmentation Data augmentation plays an important role in advancing deep learning (DL) models in numerous applications [10]–[12]. 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 more channels to the input image [13]. Albumentations, a versatile library, facilitates efficient task-specific augmentations, eventually optimizing model performance [14].

Domain Adaptation To improve the generalization capacity of models, we use domain adaptation by adapting the domain change of the source or target data [12]. 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 [7], CycleGAN modifies image styles to align with specific disaster types [15], and domain adversarial training facilitates domain-invariant feature learning for robust cross-domain generalization [15]. 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 [16].

The existing literature reveals that models trained on xBD data struggle to generalize across multiple damage classes. Furthermore, as far as we know, there is no augmentation method specifically designed for building damage detection that can be used in all types of architectures. The main contribution of this paper is to address the above mentioned research gap. Specifically, we propose to use a fusion-based augmentation technique to enhance the model's ability to detect building edges. Additionally, we demonstrate how this augmentation strategy, combined with domain adaptation techniques, improves model performance on out-of-domain datasets.

III. Methods & Materials

In this section, we described our proposed methodology, which utilized state-of-the-art data augmentation and domain adaptation strategies to improve the performance of damage assessment as described in Fig 1. We describe each part in detail as follows.

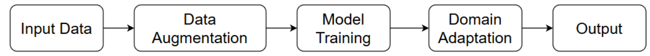


Fig. 1: Block Diagram of Proposed Methodology

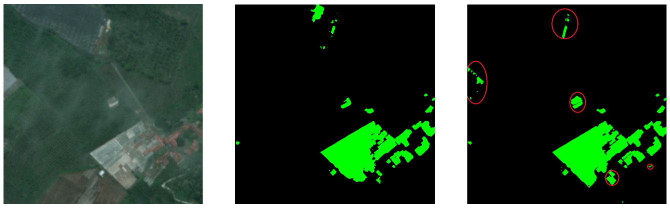
A. Data augmentation

Fusion-based data augmentation, as described in the original work [13], is a technique that enriches input data by fusing auxiliary channels or custom bands with each training instance, enabling a spectral-spatial fusion process. Unlike traditional instance-based geometric augmentation, which alters images through methods like rotation, cropping, masking, flipping, or noise addition, fusion-based augmentation enhances the data by introducing additional spectral or spatial information to the input images. This approach increases the data's dimensionality rather than merely expanding the number of training samples [13]. In fusion-based augmentation, edge detection is one of the important methods that emphasizes the structural features of an image, particularly in cases where buildings are confined to a few pixels in satellite images. By identifying edges through the maximum and minimum of the image's first derivative, this method highlights areas of significant intensity changes, aiding the model in capturing the edges and corners of objects critical for damage detection [17]. Another method, contrast enhancement, improves the visibility of objects by making them stand out more clearly against the background. Techniques like adaptive histogram equalization were used to reveal subtle details that might otherwise go unnoticed by the model [13].

To evaluate the effectiveness of this fusion-based augmentation, experiments were conducted on the xBD dataset. Grayscale scenes were generated to derive unsharp masks, contrast-enhanced images, and gradient edge bands, which were then combined with RGB channels into a stacked representation. These stacked channels underwent preprocessing based on the top-3 winning solutions of the xView-2 competition before model training and evaluation. Fig. 2 compares the localization outputs for the top-1 winning solution of the xView-2 competition. Fig. 2a displays a post-disaster image, while Fig. 2b shows the localization output before applying the proposed augmentation, where the model failed to predict the presence of all buildings in the input satellite image. In contrast, Fig. 2c demonstrates the localization output after implementing the fusion-based augmentation, effectively identifying edges and corners of buildings with improved accuracy.

B. Domain Adaptation

Domain adaptation focuses on adapting a model trained in one domain (source domain) to perform effectively in



(a) Post Disaster Image [6]

(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. Fig. 2a is a post-disaster image. Fig 2b is the output of winning solution. Fig 2c is the output after adding the proposed methodology (the improvements are marked in red circular highlights.)

a different but related domain (target domain). The main challenge in domain adaptation arises from the domain shift or domain discrepancy, which refers to the differences in the statistical distributions or characteristics of the data between the source and target domains. The goal of domain adaptation is to reduce this gap by enabling the model to generalize its knowledge from the source domain to the target domain in the supervised and unsupervised domains. This is particularly useful in scenarios where obtaining labeled data for the target domain is expensive, time-consuming, or impractical. We used two types of domain adaptation methods: supervised and unsupervised, as described below.

1) Supervised Domain Adaptation: This method is also commonly referred to as transfer learning. In this approach, a small amount of labeled data from the target domain is available. The model is fine-tuned using this labeled data while leveraging its pre-trained knowledge from the source domain. Fine-tuning is a transfer learning technique that leverages a pretrained model (in this case, the top-1 winning solution) by adapting its learned parameters to a new target domain. During fine-tuning, the weights of the pretrained model are updated using data from the target domain, enabling the model to adapt to new domain-specific characteristics while preserving the generalizable knowledge acquired from the source domain [7]. In our experiment, we fine-tuned the model using 30% of the Ida-BD dataset, demonstrating the effectiveness of this method in adapting to the domain shift.

2) Unsupervised Domain Adaptation: We used a deep CORAL (Correlation Alignment) unsupervised domain adaptation approach. In real-world scenarios, obtaining labeled datasets with proper annotations for building damage is often impractical. Therefore, models must be capable of generalizing to new disasters where no labeled data is available. CORAL helps address these domain shifts by mapping feature distributions between source and target domains without labeled data [18]. In the deep CORAL method, a new loss term has been added to the training to minimize the distribution gap between the source and target domain. This loss term computes the Frobenius norm (atrix distance function) of the difference between the covariance matrices of the source and target features in the domain:

$$L_{\text{Coral}} = \frac{1}{4d^2} \|C_S - C_T\|_F^2 \tag{1}$$

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:

$$L = L_{\text{Class}} + \sum_{i=1}^{t} \lambda_i L_{\text{Coral}} \tag{2}$$

- 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. We used λ_i=2.5 in our experimentation.

IV. Experimental Setup

This section describes the databases used, benchmark systems, and figure of merit used to gauge system performance.

A. Dataset

We employed two datasets described as follows:

1) xBD dataset: The xBD dataset is one of the most extensive and diverse datasets available for building damage detection and assessment using satellite imagery. Prior to its introduction, datasets in this domain were narrow in scope, often focusing on specific disaster types such as floods, earthquakes, or fires, and lacked standardized damage classification criteria. These limitations hindered the development of generalized and robust models for disaster response. To address these challenges, the xBD dataset provides a comprehensive collection of high-resolution satellite images that span a wide range of disasters, covering 45,362 km^2 across 19 natural disaster events worldwide [6]. The xBD dataset consists of pre- and post-disaster satellite imagery annotated with detailed building footprints and corresponding damage levels. It includes 850,736 annotated building instances, classified into four damage categories: no damage, minor damage, major damage, and destroyed [6]. We used the same set of training, test and validation set as given by xView2 competition to ensure consistent benchmarking of models across different methodologies. [5].

2) Ida-BD dataset: The Ida-BD dataset is a valuable resource for the disaster response and remote sensing communities. The Ida-BD dataset, created by Kaur et al. [7], is a high-resolution satellite imagery dataset developed specifically for building damage classification. It consists of 87 pairs of pre- and post-disaster satellite images captured during Hurricane Ida in 2021, which caused extensive damage in Louisiana, USA. The dataset provides very high-resolution imagery at 0.5 meters per pixel, offering exceptional detail for analyzing structural damage and classifying building conditions before and after the disaster. The dataset is annotated with building footprints and damage labels, enabling the classification of buildings into various damage categories, such as "no damage," "minor damage," "major damage," and "destroyed."

B. *Figures of Merit*

To evaluate the model's performance, we used the weighted F1 score, which provides a harmonic mean of precision and recall [19]. The F1 score is defined as:

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

where:

- **Precision** refers to the proportion of instances correctly classified as positive by the model out of all instances it predicted as positive instances [19].
- **Recall** measures the proportion of actual positive instances that the model correctly predicted [19].

For imbalanced datasets, the weighted F1 score adjusts the F1 score calculation by incorporating the support (number of instances) of each class:

$$F1_{\text{weighted}} = \sum_{i=1}^{n} \frac{n_i}{N} \cdot F1_i \tag{4}$$

where:

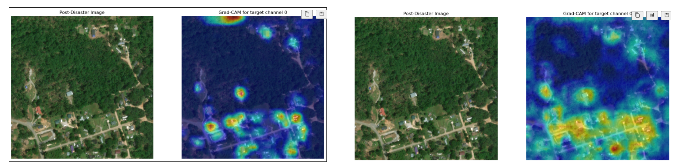
- n_i is the number of instances in class i.
- N is the total number of instances across all classes.
- $F1_i$ is the F1 score for class i.

TABLE I: Performance comparison of three benchmark systems with and without data augmentation across 5 classes. (C1:Localization, C2:No Damage, C3:Minor Damage, C4:Major Damage, C5:Destroyed)

Class	N/w1	N1+Aug	N/w2	N2+Aug	N/w3	N3+Aug
C1	0.8621	0.8945	0.8531	0.8926	0.8465	0.8827
C2	0.9147	0.9391	0.9018	0.9364	0.9071	0.9295
C3	0.6385	0.6958	0.6181	0.6831	0.6173	0.6670
C4	0.7819	0.8159	0.7702	0.8062	0.7651	0.8012
C5	0.8542	0.8825	0.8486	0.8740	0.8462	0.8746

C. *Benchmark systems*

The benchmark systems used for evaluation in this study comprise three winning solutions from the xView2 competition, each employing distinct neural network architectures for building localization and damage classification. The first winning solution utilized a simple U-Net-like architecture for building footprint segmentation, which follows an encoder-decoder design to deliver precise localization by using an ensemble of models like ResNet34, seresnext50, DPN92 as the backbone [20]. The second winning solution also implemented a U-Net-like architecture for localization but enhanced its performance by incorporating pretrained encoder backbones, specifically DPN92 and DenseNet161 [21]. The third winning solution relied on a U-Net-like architecture for localization, similar to the previous solutions, ensuring reliable segmentation. However, for damage classification, it adopted an ensemble of semantic segmentation models, combining predictions from networks with ResNet, DenseNet, and EfficientNet backbones [22].



(a) Before augmentation (b) After augmentation

Fig. 3: GRADCAM visualization of model predictions of building damage levels before and after proposed augmentation.

V. Experimental Results and Discussion

A. *Effect of data augmentation on the benchmark systems*

As shown in Fig. 3, the effect of augmentation demonstrates its impact on the model's focus areas. The results in TABLE I display the performance of these winning solutions on the competition's test split before and after applying the proposed methodology. In TABLE I, N/w1, N/w2, and N/w3 represent the first, second, and third winning solutions, respectively. N1+Aug, N2+Aug, and N3+Aug represent the first, second, and third benchmark systems with augmentation methods. On average, the fusion-based augmented model performance has improved by 5-7% in minor damage and major damage classes, 2.5% improvement in localization, and a modest 1% improvement in the no-damage class. This demonstrates that fusion-based augmentation in combination with geometric augmentations is effective in improving building damage classification. The code for this project is available at GitHub Repository [23].

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

In this experiment section, we explore the effectiveness of fusion-based augmentation along with supervised and unsupervised domain adaptation explain in section III-B. The Ida-BD dataset was chosen for this purpose, providing a suitable test case due to its significant domain differences from the xBD dataset. The experiments utilized the first winning solution [2] from the xView2 competition. All models were pretrained on the xBD dataset before applying various

TABLE II: Performance comparison of different methods on the unseen xBD dataset in terms of weighted F1 score. (DA: Domain adaptation), The proposed methods are indicated with an asterisk (*)

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+Supervised DA fine-tuning	0.8419	0.6724	0.2923	0.1837	0.0954
Pretrained model+Supervised DA fine-tuning+Augmentation*	0.8485	0.6961	0.3147	0.1920	0.117
Pretrained model+ + unsupervised DA-CORAL	0.8146	0.6581	0.2753	0.1346	0.059
Pretrained model+unsupervised DA-CORAL+Augmentation*	0.8215	0.6641	0.2816	0.1452	0.0631

training configurations. Six distinct training setups were tested to assess the performance of fusion-based augmentation with domain adaptation in out-of-domain scenarios as described in TABLE II. As shown in TABLE II, the results consistently demonstrate that the inclusion of fusion-based augmentation enhances model performance across all configurations. Models trained with fusion-based augmentation exhibited improved accuracy in detecting building edges and corners, resulting in more precise building localization and damage classification. The improvements demonstrate the importance of using the fusion-based data augmentation method. This approach enhances the model's ability to generalize to out-of-domain datasets, even in scenarios with significant domain shifts, ultimately improving its performance in building damage detection and classification tasks.

VI. Conclusion And Future Work

This paper focuses on the use of deep learning-based techniques, including data augmentation and domain adaptation, for robust building damage classification after disasters. The research emphasizes the limitations of current state-of-the-art models in effectively generalizing across all building damage classes. To address these challenges, we proposed a system incorporating a fusion-based augmentation strategy. To further assess the generalization capabilities of the proposed method, we applied it to the Ida-BD dataset, leveraging domain adaptation techniques such as supervised fine-tuning and unsupervised Deep CORAL. Results showed that models trained with fusion-based augmentation and domain adaptation achieved superior localization and classification accuracy, even in out-of-domain scenarios. The current work is limited only to networks with CNN as a backbone and is tested on the Ida-BD dataset. Our future work is focused on evaluating the fusion-based augmentation on transformer networks and evaluating unseen disaster types.

Acknowledgment

The authors acknowledge funding support for this work from Kansas NSF EPSCOR Research and Education Innovation grant.

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