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Deep Learning for Rapid Identification and Assessment of Disaster Areas Based on Satellite Images

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Abstract: Natural disasters affect 350 million people annually, in addition to financial losses amounting to billions of dollars. When these disasters occur, a quick and accurate response is extremely important. Therefore, obtaining correct information about damage locations leads to a rapid and effective response by rescue teams, thus saving the largest number of lives. Rescue teams rely on satellite images to determine the affected locations, in addition to the severity of the damage and its causes. However, rescue teams need to follow a specific approach that enables them to analyze huge amounts of satellite images accurately and quickly, which represents a major challenge for them. Deep Learning can be used to overcome these challenges and provide assistance and support efforts. In this research, Siamese U-Net deep learning system with attention technique was applied on two groups of satellite images (pre- and post-disaster) for semantic segmentation of buildings and damage level classification. Two-stream of U-network was used to generate a buildings segmentation mask as a first step. Then, the decoder extracts high-dimensional feature vectors through various operations to generate damage classification mask. Self-attention modules were included to capture important information, thus enabling the system to focus on the areas surrounding buildings. The proposed system was evaluated on xBD, a benchmark dataset for building damage assessment, and achieved the best segmentation and classification results by conducting several numerical and visual comparisons with related works that used the same dataset, and it also provided a higher degree of generalizability and reliability.

Keywords: Disaster damage assessment, Satellite imagery processing, Semantic segmentation, Siamese network, Deep convolutional neural network.

1. Introduction

Natural disasters cause great economic, social and material devastation, and their effects extend for years to come. In 2019, USA was exposed to 14 natural disasters, each of which caused losses estimated at one billion dollars [1]. But the real loss is the loss of lives. According to recent statistics, the natural disasters kill more than 90,000 people annually, and they directly affect more than 350 million others [2]. According to World Health Organization (WHO) report, the Turkey-Syria earthquake alone killed more than 35,000 people [3]. Given environmental analysis of climate, natural disasters will increase in number and severity due to the rise of greenhouse gas emissions and volatile climate changes [4]. Therefore, we need to develop emergency plans and create the necessary requirements for disaster recovery. Taking into account that the areas affected by disasters are difficult to reach and are often isolated, which requires using of optimal route determination techniques to reach the goals quickly [5].

This requires the development of reliable techniques and programs that keep pace with these events to help specialized rescue teams and emergency responders identify the most affected areas that need urgent operations to evacuate citizens trapped in damaged buildings and treat the wounded [6]. The process of counting and evaluating the extent of damaged buildings at or after the disaster occur is considered one of the most important steps when carrying out relief and humanitarian missions. Which is often difficult and poses an immediate danger to people on the ground [7], [8]. This requires finding alternative solutions to do this remotely. Therefore, this study aims to assist humanitarian relief teams in rescue and recovery missions, aid routing, and resources allocation to areas stricken by natural disasters,

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by using deep learning techniques on very high resolution (VHR) satellite images to evaluate buildings and estimate damage levels.

Commercial satellites are constantly increasing around Earth orbit. The companies that own these satellites, like DigitalGlobe company [9], are constantly improving the generation of (VHR) satellite images, which in turn provide accurate assessments of damage levels in buildings [10] and high accuracy in identifying and tracking targets [11]. With the development of machine and deep learning methods, it became possible to analyze a huge number of categorical data, text data, time series data and numerical data like VHR images [12]. This will speed up the assessment of damaged areas and facilitates relief operations when disasters strike. In this research, a Siamese U-net system is proposed to extract vector features from a pair of satellite images, and then generates a mask (map) with semantic segmentation of buildings and classification of damage levels, as shown in Fig. 1.

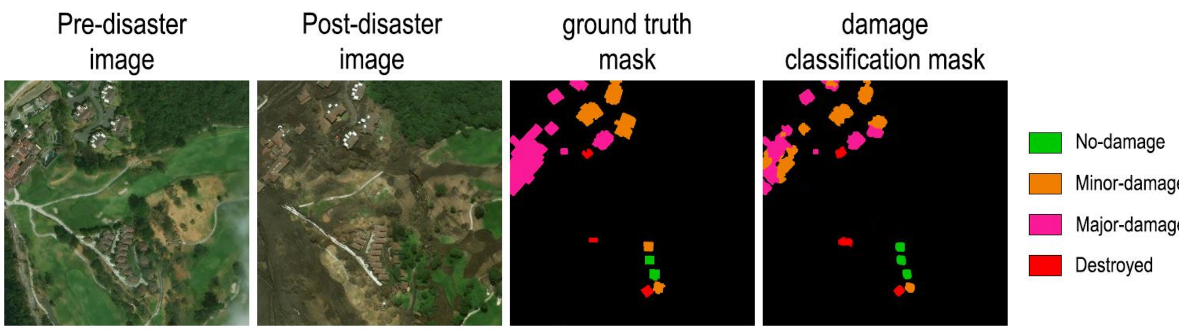

Figure 1. Sample (pair of images and ground truth mask) from xBD dataset, and damage classification mask of the proposed system

The main contributions of this research are:

- Developing a Siamese deep learning network with remote sensing for accurate classification of buildings damage levels based on satellite images.
- Modifying the U-net model to generate a pair of binary buildings segmentation masks, in addition to damage classification mask, to facilitate comparison between pre- and post-disaster images.
- Employing self-attention techniques to focus on the areas surrounding buildings and accurate classification, especially in disasters that do not cause direct damage to buildings, such as floods.

The remaining part of this research is structured as follows: Section 2 presents literature review of various DL-based disaster damage assessment methods. Section 3 explains the proposed methodology and Siamese U-net architecture, in addition to a detailed explanation of the dataset used and training settings in this research. Section 4 presents the numerical and visual results and comparisons of the proposed system and comparative works, in addition to a detailed discussion of the above. Finally, Section 5 explains the conclusion of the research.

2. Literature Review

Standard assessment systems, used to evaluate disaster damage and provide fast and accurate classification results, require training for all types of natural disasters. Much of the literatures focuses on designing a damage assessment system for one type of disaster. While other literatures provide a binary classification of buildings, damaged and undamaged [13], [14].

The authors of [15] proposed the use of machine learning techniques to assess building damage resulting from earthquakes. They used decision tree, random forest, support vector machine, K-nearest neighbor and artificial neural network techniques to predict buildings damage based on simulated earthquake dataset. While the performance of the proposed machine learning techniques was evaluated on a real dataset of building damage resulting from the Nepal earthquake in 2015.

One of the difficult challenges facing researchers is evaluating buildings damaged by flood and tsunami disasters [16]. The evaluation process based only on detecting damage to the building’s surface is considered an inaccurate procedure, as it requires a survey of the areas surrounding the buildings as well. A Convolutional Neural Network (CNN) was used by [17] to scan interior and exterior landmarks and features of buildings after a flood. To test the performance of the proposed model, the researchers relied on the “Heavy rainstorm in Zhengzhou” dataset to classify flood damage levels in rural homes. The proposed model provided higher accuracy results compared to ResNet-50 [18] and MobileNet-v2 [19] by supporting it with visual analysis of image features.

Datasets that containing satellite images used to assess damage of buildings were limited to one type of natural disaster like fires [20], hurricanes [21], floods [22] or earthquake [23]. While xBD was designed as the first dataset containing the largest number of natural disasters [24]. xBD is a benchmark large-scale dataset that used in the problems of building damage estimation and change detection resulting from natural disasters. It contains 22,068 VHR satellite images that collect from various disasters like hurricanes, floods, fires, earthquakes and volcanoes. In addition, it provides ground truth masks with four classes of buildings damage. The authors proposed the xBD baseline, which consist of two networks, for disaster damage assessment. They first fed the U-Net with a post-disaster image for building segmentation, and then fed the ResNet-50 with a post-disaster image for damage classification.

In fact, deep neural networks are used in the field of building damage assessment through two tasks: building segmentation based on pre-disaster images, and damage level assessment based on post-disaster images. Some researchers have addressed the use of the two tasks separately and sequentially (one- stream) [25].

Two different networks were used to perform the segmentation and classification tasks separately in [26]. In the first step, an image before the disaster occurs is entered into the U-net model (based on ResNet-50) to generate a binary map for the background and buildings. The ResNet-50 encoder based on 3 successive blocks, which repeated 3, 4, and 6 times for the block 1, 2, and 3, respectively. In the second step, the detected buildings are separated and fed into the EfficientNetv2 [27] model individually with a 224-pixel image. Instead of classifying all the buildings together within the map, each building has been clipped individually and then classified into 1-of-4 damages classes. They fed their network using the first tire of xBD dataset, which contains only 7 of the 19 disaster types in xBD. The results were IoU=0.608 for segmentation and F1=0.731 for classification.

Conversely, other researchers exploited the relationship between pre- and post-disaster images to process both segmentation and assessment simultaneously (two-streams). The important features are extracted from the two images and then merged by concatenation [28] or subtraction [29].

In [30], the researchers proposed using a single convolution-based network for both segmentation and classification tasks. Based on a pair of pre- and post-disaster images from xBD dataset, features in each layer were extracted to generate a multiple feature map using the Feature Pyramid Network (FPN). Then, the Mask R-CNN network is fed with these features to perform the localization and classification tasks simultaneously. By extracting 512 features from the input image, their proposed network achieved F1=0.835 for localization and F1=0.697 for classification. In this paper, we proposed a Siamese U-net system with a self-attention module that identifies and evaluates disaster-affected areas through semantic segmentation and damage levels classification of VHR satellite images.

3. THE PROPOSED METHOD

This section describes the designing Siamese U-net architecture for building semantic segmentation and damages levels classification. One part of this architecture is the U-net [31], which receives an input image and performs analysis and processing on it to generate a buildings segmentation mask as a first step. These operations done in the encoder, which consists of a set of sequential blocks. In this research, 2-encoder with 5-block were adopted to extract features from two pairs of input images, pre-disaster (I-pre) and post-disaster (I-post), see Fig. 2.

In each block a pair of 3 x 3 2D-convolution were used, non-linearity ReLU activation function and batch normalization. Then followed by dropout (0.2) to reduce the overfitting. Due to the large number of parameters and computations resulting from the network structure, the dimensions were significantly reduced (downsampling) at the end of each block by using a 2 x 2 max-pooling. The number of features produced at the end of each block doubled, starting with 64 in the first block and reaching 1024 in the fifth block. The U-net model was modified and used again inversely to generate two pairs of masks (M-pre and M-post) to facilitate comparison between the I-pre and I-post disaster input images.

On the decoder side, the green region of the Fig. 2, the process is reversed. Where the dimensions are increased (upsampling) using 4 x 4 2D-convolution-transpose, in addition to using 3 x 3 2D-convolution, ReLU and batch normalization layers. Besides restoring the initial pixel resolution of the raw image, the U-net concatenates and shares local information of the features from the blocks of the 2-encoder and the new decoder using skip connection. Therefore, the decoder extracts high-dimensional feature vectors from this information to generate damage classification mask (M-damage) through concatenation and 2D-convolution operations. This is the second step in the proposed system. The feature vectors created by the U-net encoders and the independent decoder represents the Siamese net which reduced the size of the model and the number of learned parameters along training phase in comparison to [26], [30].

In addition, self-attention modules were placed in the Siamese net which helps it focus on the different shapes and areas surrounding target buildings when evaluating and assessing damage. The attention gates were introduced by [32] to help image analysis by capturing important features and information passing over skip connections. The importance of this step is evident in cases of flood and tsunami disasters which may not lead to damage to the roofs of buildings. But the surrounding water causes major damage inside buildings and leads to great loss of life especially in small urban and rural homes compared to rise buildings.

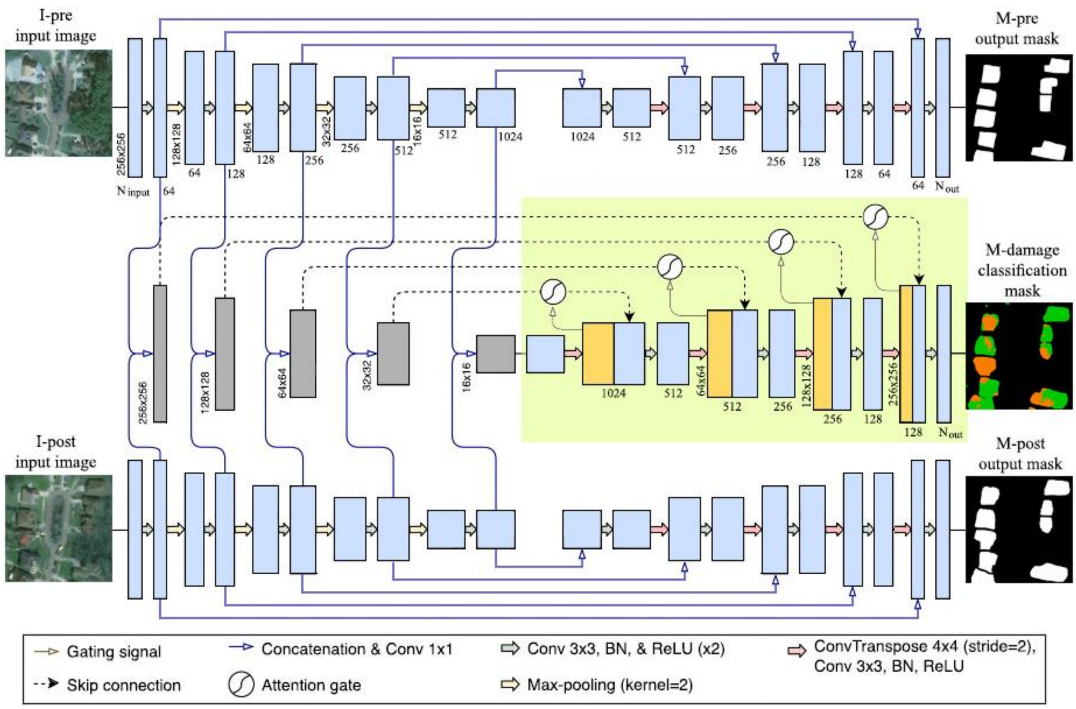

Figure 2. The architecture of the proposed Siamese U-net system with self-attention module

Finally, from the last feature vector z we obtained the required number of classes *N* using softmax activation function (1). The network then produces a vector with predicted probability values P(z) for N-of-classes (2). Then, the final classification output y of the input image was computed using the maximizing (3).

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{n=1}^{N} e_n^z} \quad (1)$$

$$p(z) = [p(z)\,, p(z)\,, \dots\,, p_N(z)] \quad (2)$$

$$y = \max p(z) \quad (3)$$

A. Dataset

Dataset used in the process of training and testing the proposed system has a major impact in designing the system and obtaining good, realistic and reliable results. xBD [24] is a benchmark large-scale dataset that used in the problems of building damage estimation and change detection resulting from natural disasters. One of the xBD characteristics is that it provides 22,068 VHR satellite images (1024*1024 pixels) covering an area of 45,362 km2 and contains 850,736 buildings. These data were collected from 19 natural disaster events as shown in Fig. 3, and for these reasons it's considered the largest dataset in this field to date. The xBD dataset was used in this research for the following reasons:

- xBD covers several types of natural disasters such as hurricanes, floods, fires, earthquakes and volcanoes. This represents a challenge when designing DL model for different disasters types.
- Datasets often provide only two levels of damage: "damaged" or "undamaged". While xBD provides masks building polygons with 4 levels of damage: (No-damage, Minor-damage, Major-damage, Destroyed).
- The layout of buildings varies in terms of shape, size, and density from one region to another, and thus the damage of buildings varies with different regions. That's why xBD focused on including samples from different locations around the world as shown in Fig. 3.

B. Training sitting

One of the U-net pros when compared to fully convolutional neural networks is that it has a lightweight architecture that can work on small datasets. However, since deeper networks are considered harder to optimized and consume more training time compared to shallower networks [33]. Therefore, the weights of the first layer were initialized using the inceptionV3 network [34] that was pre-trained on the large ImageNet dataset. This contributed to achieving better convergence and improving training time.

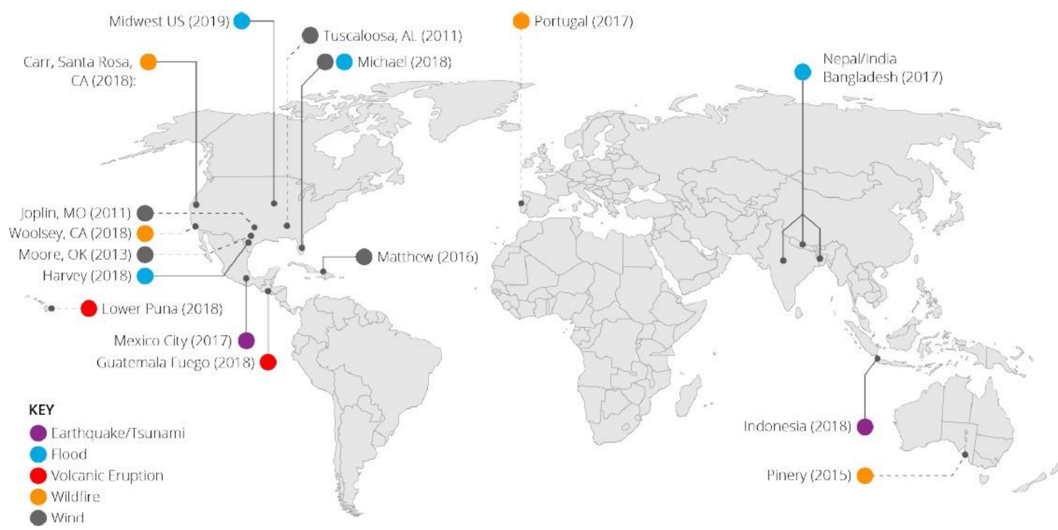

Figure 3. Map of disaster types and their distribution around the world in the xBD dataset

The entire dataset was shuffled and randomly split before sending it to the model. 15% of the dataset was hold out for model testing. The remaining 85% was split in a ratio of 80:20 for model training and validation, respectively. Thus, it was confirmed that both train-set and test-set now include different images and events, and ensuring that the model simulates performance as in a real-world scenario when it is fed images it had not seen previously.

The model is trained for 100 epochs with a batch size of 32, and the initial learning rate is 1x10-3. Several experiments were conducted on the size of the samples in each batch, where the image size was reduced from 1024 pixels to 512*512 and then 256*256. The experiments showed that having batches of 16 images with a size of 256 pixels contributes to reducing memory and time use for both training and testing, which is why it was adopted in this research. The Adam optimizer [35] is used to optimize the training process and compute the learning rate which decays until it reaches zero in the last epoch. Finally, the binary cross-entropy is used for building segmentation loss, and the categorical cross-entropy is used for damage levels classification loss.

It should be noted here that these settings were not chosen randomly, but rather many experiments were conducted to obtain the best results. The proposed system is implemented in python 3.6 with Intel (R) Core i7-7800X CPU @ 3.50 GHz and Nvidia Titan V GPU. During training phase, data augmentation and preprocessing operations like (vertical/horizontal flips, rotation, sharpening and contrast) were used to reduce overfitting and significantly enhance the building segmentation and damage classification results [36].

4. RESULTS

During the training phase, the Siamese U-net learns how to extract feature vectors from the training set and produces a map with building polygons and labeled samples for damage classes. A separate validation set is employed to evaluate the Siamese U-net during the process of adjusting the hyper parameters and throughout the training phase. Finally, the testing set is used to provide a realistic and unbiased assessment of the generalization ability of the system, because it is a separate part of the training and validation sets and the network has never seen this data before.

The Intersection over Union (IoU) metric was used for semantic segmentation. IoU is a common localization metric that used to measure segmentation accuracy and compute segmentation errors [37]. IoU computes the amount of overlap between two bounding boxes, the ground truth buildings mask bounding box (A) and the predicted buildings bounding box (B), (Eq. (4)). A high IoU value indicates that there is a good match in buildings between the ground truth mask and predicted mask, where a score of 1 represents a perfect match. The opposite is true, as a low IoU value indicates that there is little match in buildings between the ground truth mask and predicted mask.

$$Intersection\ over\ Union\ (IoU) = \frac{A \cap B}{A \cup B} \quad (4)$$

For damage levels classification, there are many metrics that are used to monitor system performance. The Accuracy metric is flawed and inappropriate for the imbalanced xBD dataset, which will predict more than 70% towards “no damage” because it represents 75% compared to the quantity of the other classes. While F1-

score is a suitable metric for the imbalanced xBD dataset. The performance of Siamese U-net was evaluated during the training using F1-score (Eq. (5)).

$$F1 = 2 \times \frac{precision \times recall}{precision + recall} \quad (5)$$

TABLE I. COMPARISON RESULTS OF THE PROPOSED SYSTEM AND COMPARED WORKS USING IOU AND F1 FOR SEMANTIC SEGMENTATION AND DAMAGE LEVELS CLASSIFICATION, RESPECTIVELY

Model	IoU segmentation	F1 No-damage	F1 Minor-damage	F1 Major-damage	F1 Destroyed
xBD baseline [24]	0.80	0.663	0.143	0.010	0.465
U-net_EfficientNetB4 [26]	0.72	0.898	0.438	0.547	0.739
Mask R-CNN_FPN [30]	0.83	0.906	0.493	0.722	0.837
Siamese U-net [our]	0.88	0.918	0.643	0.796	0.851

Table 1 shows the performance results of Siamese U-net on the testing set for both semantic segmentation (using IoU) and damage levels classification (using F1-score). To demonstrate the strength of the proposed system, a comparison was made with works [26], [30]. These works were chosen because their architecture is similar to the proposed model, it based on CNN which is the basis for U-net, and they used the same xBD dataset. Also, because their code is available online, which facilitates the process of configuring the training settings for all works, thus we ensure objectivity and fairness when comparing. Table 1 also shows the numerical results of the comparison between the proposed system and compared works [26], [30] and xBD baseline too [24].

We can see from the table that our proposed system achieved superior results for both semantic segmentation and damage levels classification and for all damage categories compared to [26], [30] and xBD baseline [24].

It is clear from the table that all models achieved the best performance in classifying no-damage buildings. But the real challenge lies in classifying buildings with minor-damage, as these damages do not appear clearly on the surfaces of the buildings, which is why all models achieve the lowest levels of accuracy in classifying these buildings.

We observed that models classify damage levels for buildings with minor-damage as building with major-damage, which leads to lower recall rate and hence lower F1 score. This is due to the occurrence of some confusion in the models when extracting the semantic features surrounding the buildings. Buildings are classified as minor-damage when they are located in areas of fires, volcanic flows, or floods, and these same buildings are classified as major-damage when they are completely surrounded by these elements, as damage assessment experts mention in [38].

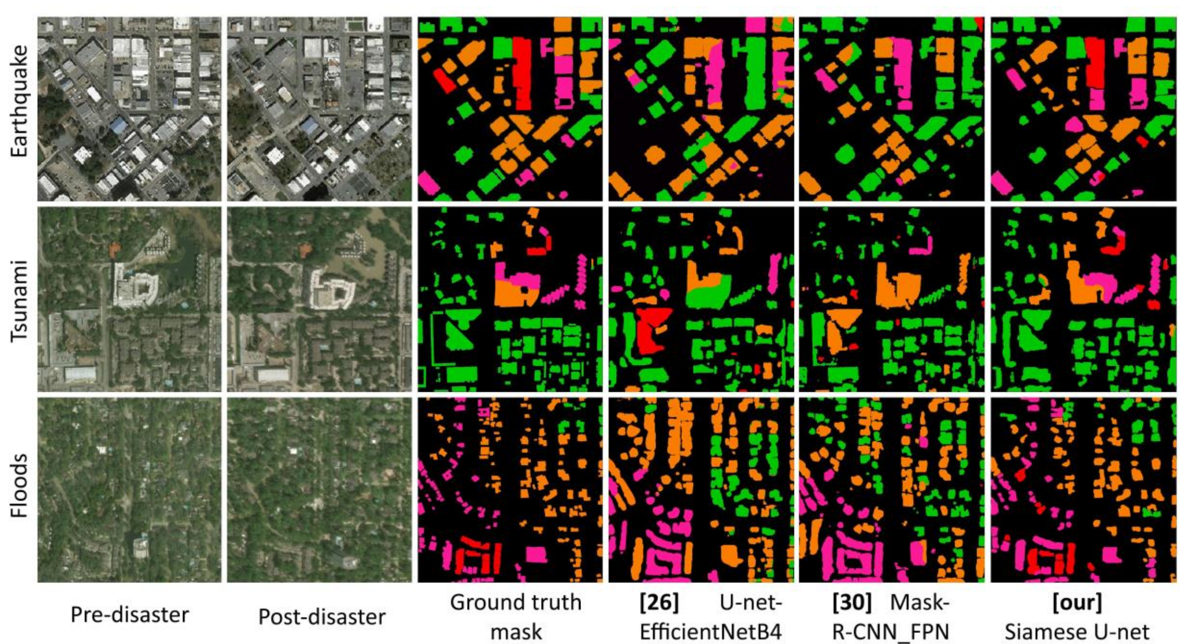

Figure 4. Visual comparisons of building segmentation and damage classification of the proposed Siamese U-net and compared works

Fig. 4 shows a visual comparison of three different samples (an earthquake, tsunami and flood) from the testing set for the proposed system and the compared works [26], [30]. The colors of segmentation mask are: black (area outside building), green (no-damage), orange (minor-damage), pink (major-damage) and red (destroyed). Because the xBD baseline achieved poor results, it was excluded from the visual comparison.

The results appear in Fig. 4 that all the works succeed to different extents in detecting and segmenting most of the buildings. However, our proposed method excels in achieving the highest accuracy to draw building boundary.

For building segmentation, the proposed system provided higher segmentation results than the compared works. As we noted in Table 1 of the matching results between the ground truth mask and predicted mask (IoU segmentation), This is also shown in Fig. 4. Where the proposed system identifies all buildings and crops them close to the size and shape of the ground truth mask. The reason for this is that the proposed system used semantic segmentation of buildings instead of just localization. This is done by first detecting the buildings in the image, then drawing a border around it (localization), and finally gathering the points of each building using a segmentation mask. In addition, we cropped each satellite image with a size of 1024*1024 pixels into 16 new images with a size of 256*256, instead of just resizing the image itself to 512*512 or less. This had a significant impact on segmentation of very low-resolution buildings, as well as reducing memory and time usage for both training and testing.

For damage levels classification, the proposed model significantly outperformed the compared works. Here the benefit of the concatenation operation appears, which we used in the encoder part for both pre- and post-disaster images in order to preserve information and important features for detecting and classifying buildings. While the compared works do images subtracting and concatenating only in the decoder part. As mentioned in section 3, The self-attention module utilizes feature vectors to capture long-range information from buildings and their surroundings as well, this had a significant impact on the damage classification process. Moreover, the use of data augmentation and pre-processing operations such as (vertical/horizontal flip, rotation, sharpening and contrast) enhanced the segmentation and classification processes.

Regarding false alarms, the proposed model succeeds in avoiding the detection of two false alarms compared to the works which failed to avoid them as we can see in the lower right region of the images in the first row. This issue was repeated again in the third row and along the right side of the images for the compared works.

It is clear from the numerical and visual comparisons that work [26] obtained the lowest results. This is because the researchers first fed the U-Net with a post-disaster image for building segmentation. Then for damage classification, they fed the EfficientNetB4 with a 224-pixel image of each individual building. In addition, their encoder consists of 3 successive blocks, which repeated 3, 4, and 6 times for the block 1, 2, and 3, respectively. Such complexity method (not end-to-end trainable) with deep networks leads to the phenomenon of disappearing gradients, as a result of the very slow decrease in gradient values, and thus hinders the convergence process in the network. Which negatively affected the segmentation and classification processes.

We conclude from the above that our proposed Siamese U-net outperforms the methods proposed by the works [26], [30] in the damage levels classification by a large margin.

Looking at the third row in Fig. 4 we notice a difference in the angle of taking the pre- and post-disaster images. There are also many buildings covered by trees, which partially obscure the process of detecting the buildings. This prompted us to conduct a new comparison to discover the accuracy of the performance of the proposed model.

Fig. 5 presents three challenges between the proposed model and compared works. The first challenge involves detecting the cloud-covered building that appears at the bottom of the image in the first row. The compared works fail to detect this building, while the proposed model succeeds in detecting it despite the difficulty of seeing this building with the naked eye.

The second challenge involves detecting buildings in two images taken at different viewing angles from the sensor to the ground, thus causing a slight change in the look of the scene. The compared works succeed in classifying most buildings but fail to detect two buildings located at the top of the images. While the proposed model succeeds in detecting these two buildings.

The last challenge includes detecting buildings partially covered by trees and their shades. It is clear from the images in the third row that the compared works failed to detect some buildings covered with trees. While the proposed system succeeds in detecting all buildings, even those covered by trees.

It is clear from all previous comparisons that our proposed Siamese U-net, which simultaneously segment and assess building damage levels, succeeds with high accuracy in different disasters and for various visual challenges, while the compared works fail to reach this accuracy and evaluate the damage correctly.

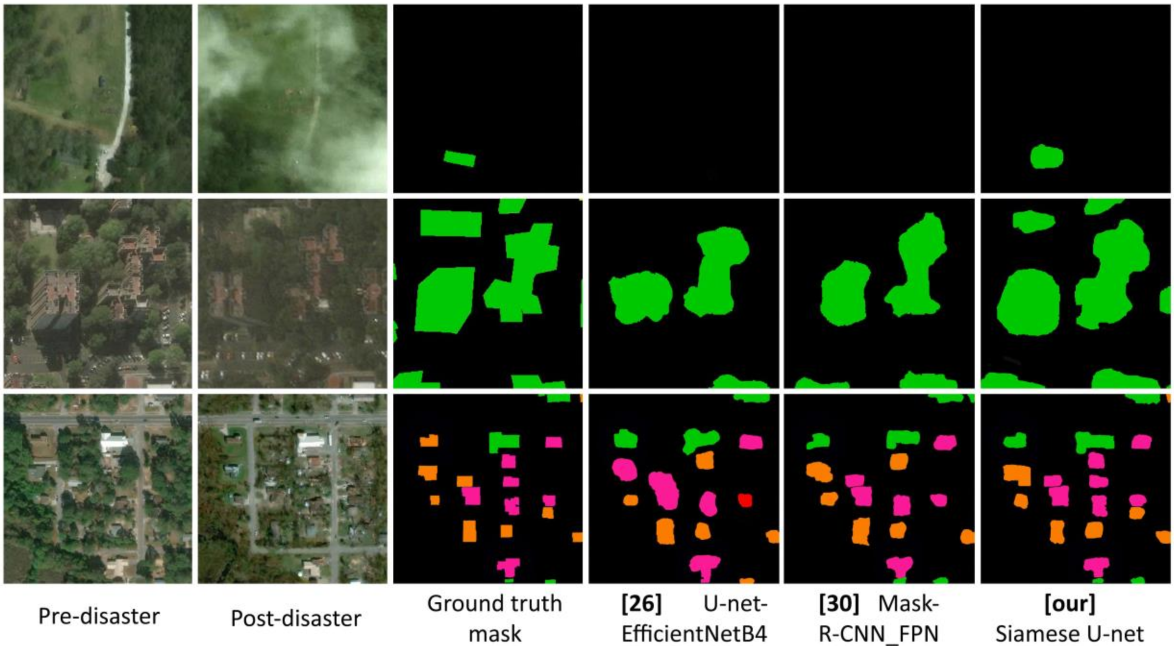

Figure 5. The robustness of the proposed Siamese U-net in assessing damage

5. Conclusion

The frequency of natural disasters continues to increase, causing a lot of loss of life and property. Rescue teams are trying to use all modern techniques to evacuate people affected by these disasters first and then to deliver the necessary food and medical aid. This paper aims to present a system based on deep learning to identify and assess damages in sites affected by these disasters. In this study, we proposed a Siamese U-net DL system with self-attention technique for semantic segmentation of buildings and classification of damage levels. The proposed system trained and tested on xBD satellite imagery dataset. With the use of pre-processing techniques on pairs of pre- and post-disaster images, the U-net model has proven its efficiency in building segmentation. Then the Siamese network with attention techniques provided the best results in generating damage levels classification masks. The performance of the proposed system was compared with a number of related works that used the same dataset, and the results were much better than the compared works.

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