Building Damage Segmentation After Natural Disasters in Satellite Imagery with Mathematical Morphology and Convolutional Neural Networks

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Abstract: In this study, our main motivation was to develop and optimize an image segmentation model capable of accurately assessing damage caused by natural disasters, a critical challenge today where the frequency and intensity of these events are increasing. In order to predict damage categories, including *no damage*, *minor damage*, and *major damage*, we compared several models and approaches. we explored and compared several models, focusing on the Unet architecture employing BDANet and other architectures such as ResNet18, VGG16, and ResNet50. Layers with mathematical morphology operations were applied as a filtering strategy. The results indicated that the Unet model with the BDANet backbone had the best performance, with an F1-score of 0.761, which increased to 0.799 after applying mathematical morphology operations.

1 INTRODUCTION

Image segmentation is a fundamental technique in the field of image processing and computer vision that involves dividing an image into meaningful and non-overlapping regions. The process of image segmentation is essential for natural scene understanding, as it allows for the identification of objects and their boundaries within an image (Yu, 2023).

The importance of image segmentation lies in its ability to extract relevant information from an image, which can be used for various applications such as object recognition, image compression, and image enhancement (Li et al., 2020).

One such application of image segmentation is in assessing damage to buildings and in identifying landscape changes before and after natural disasters. This allows the location and identification of buildings and other structures, which can then be analyzed for damage.

A neural network can be used to locate the most affected areas and segment damage to buildings (Da et al., 2022). Similarly, Wang (Wang and Li, 2022) used automatic image segmentation technology to identify comprehensive disaster reduction capability assessment of regional disaster hotspots. However, to perform this task of image segmentation after natural disasters, the availability of datasets that have pre and post-disaster quality annotations is crucial.

The xBD dataset, is widely used to evaluate building damage segmentation from satellite imagery (Gupta et al., 2019). This dataset includes high-resolution satellite images from 19 natural disaster events, such as hurricanes, earthquakes, floods, forest fires, volcanic eruptions, and tsunamis, covering more than 45,000 square kilometers of various natural disasters that have happened around the world.

Various neural network architectures have been used in satellite image segmentation after natural disasters. UNet is a popular architecture that uses a contraction path to capture context and a symmetric expansion path to enable accurate localization (Ma et al., 2020).

Multiscale convolutional neural network with cross-directional attention (BDAnet) is an architecture that uses multidirectional attention and multiscale feature fusion to improve building damage assessment from satellite imagery (Shen et al., 2021). Like BDAnet, the Siamese hierarchical transformer framework is another architecture that uses a segmentation network (Da et al., 2022).

The successful application of architectural models for segmenting pre and post-disaster images depends on using registered images. This presents sub-

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stantial challenges, such as the identification of stable features in multitemporal images (Lyu and Jiang, 2017) and the segmentation and clustering of planar images, both critical issues in the field of computer vision (Burdescu et al., 2014). It is also crucial to maintain the spatial relationship between these images for accurate segmentation (Da et al., 2022).

The studies from Shen (Shen et al., 2021) and Weber (Weber and Kan, 2020) propose new convolutional neural network architectures for building damage assessment from satellite imagery after natural disasters. Shen (Shen et al., 2021) proposes the BDANet, a two-stage CNN that uses multidimensional and multidirectional attention mechanisms to improve the F1-score of image segmentation. Weber (Weber and Kan, 2020) proposes an improved CNN Inception V3 architecture that combines remote sensing imagery and block vector data to assess the degree of damage of groups of buildings.

Both studies aimed to improve the F1-scores of building damage segmentation models from satellite imagery using deep learning techniques. Despite the contributions of the mentioned studies, there is still a gap regarding the exploration of mathematical morphology and different approaches for registered images in the evaluation of building damage in post-disaster satellite images.

Mathematical morphology, with its operations of dilation, erosion, opening, and closing, allows for the improvement of the mask predicted by the model, removing noise and imperfections generated by the model, thus facilitating the identification of damaged buildings.

In addition, we seek to develop and implement new approaches for handling registered images while maintaining the spatial relationship between pre and post-disaster images. This strategy will allow a more accurate comparison of the state of buildings before and after the catastrophic event, contributing to a more accurate damage assessment.

The goal of this study is to improve the segmentation of building damage from satellite images using the xBD dataset (Gupta et al., 2019), particularly in post-disaster situations, by testing different neural network architectures and by using mathematical morphology techniques as layers in the neural networks and new approaches for registered images.

2 BACKGROUND

2.1 Data Preparation Methods for Image Segmentation

Data preparation is a crucial step in image segmentation that involves preparing the image conditions to meet the segmentation requirements.

1. Cropping: select a part of the image, perform a cropping, and use it as input to the segmentation model. This technique helps to increase the diversity of the training data and avoid overfitting (He et al., 2022).
2. Data augmentation transformations: applying various transformations to the input image to create new training samples. Common transformations include rotation, scaling, flipping, color jittering, shear, translation, and color distortions. These transformations help to increase the size of the training dataset and improve the robustness of the model (He et al., 2022).
3. Resize: changing the size of the input image to match the input size of the segmentation model. This technique is useful when the input image size is different from the model's input size (Alamin et al., 2016).
4. CutMix: the technique is a data augmentation strategy proposed by Yun (Yun et al., 2019) that involves cutting and pasting patches among training images, where the ground truth labels are also mixed proportionally to the area of the patches.

2.2 Approaches for Registered Images

There are several possible approaches for segmenting registered images, such as disaster images where we have one image pre and one post-disaster.

One possible approach for segmenting registered images, such as pre and post-disaster images, is to concatenate the two input images in the channels dimension, i.e., stacking them generating an image with six channels. This approach has been used by Li (Li et al., 2019) and Muhadi (Muhadi et al., 2020). In this approach, the concatenated image is fed into a segmentation network to obtain the segmented output.

Another possible approach is to feed the pre and post-disaster separated images into a Siamese network. This approach has been used by Da (Da et al., 2022) and Chowdhury (Chowdhury and Rahnemoonfar, 2021). In this approach, the Siamese network learns a similarity metric between the pre and post-disaster images, which can be used to identify changes in the scene.

A third possible approach is to calculate the difference between the pre and post-disaster images. This approach has been used by Rudner (Rudner et al., 2019) and Yang (Yang et al., 2020). In this approach, the difference image is fed into a segmentation network to obtain the segmented output.

2.3 Neural Network Architectures in Image Segmentation

UNet is a fully convolutional encoder-decoder network architecture with skip connections between encoder-decoder modules, which was introduced by Gaj (Gaj et al., 2019).

Feature pyramid network (FPN), is a neural network architecture that was originally proposed for object detection but has also been applied to segmentation tasks (Minaee et al., 2021).

LinkNet is a neural network architecture that was proposed for semantic segmentation tasks (Basu, 2023). It is a fully convolutional network that uses a combination of encoder and decoder modules to extract features from the input image and generate the segmentation map.

PSPNet is a neural network architecture that stands for pyramid scene parsing network. It was proposed for semantic segmentation tasks and is based on a pyramid pooling module (PPM) that captures multiscale contextual information (Li, 2023).

BDAnet is a neural network architecture that was proposed for image segmentation tasks (Mochalov and Mochalova, 2019). It is a fully convolutional network that uses a combination of dilated convolutions and atrous spatial pyramid pooling (ASPP) to capture multiscale contextual information.

2.4 Mathematical Morphology

Mathematical morphology is a field of image processing that deals with the analysis and manipulation of geometric structures in images. The two primitive operations of mathematical morphology are dilation and erosion. Additionally, there are the operations of opening and closing, which are derived from the primitives (Chen et al., 2021).

Dilation is an operation that expands the boundaries of a bright region in an image, while erosion shrinks them. Opening is an erosion followed by a dilation, which can be used to remove small bright objects from an image. Closing is a dilation followed by an erosion, which can be used to fill small holes in an image (Banon and Barrera, 1994).

2.5 Visualization and Evaluation

There are several visualization and evaluation techniques that can be used to measure the results of image segmentation models. For visualization we use visual semantic segmentation (Benkhoui et al., 2021) and for evaluation of the results we use the F1-score (Laine et al., 2021).

3 METHODOLOGY

This section begins with a description of the dataset, followed by the four steps of the methodology. Data preparation, models training, application of mathematical morphology filters, and model evaluation.

The code was developed in Python and is available in GitHub for future reference [1].

3.1 xBD Dataset from xView2 Challenge

The xBD database from xView2 challenge (Defense Innovation Unit, DoD, 2023) contains high resolution satellite imagery of six different types of natural disasters around the world, covering a total area of over 45,000 square kilometers (Gupta et al., 2019).

Each pixel in the image has a value that corresponds to one of the five labels defined to classify the state of each building. These labels were defined according to the degree of damage presented by the building and are as follows: *background*, *no damage*, building with *minor damage*, building with *major damage*, and *destroyed* building. Table 1 shows the values corresponding to each damage level. The levels range from 1, *no damage*, to 4, *destroyed*. The 0 corresponds to the *background*.

Table 1: Scale of damage noted on buildings. Adapted from (Defense Innovation Unit, DoD, 2023).

Score	Label	Visual description of the structure
1	*No damage*	Undisturbed. No sign of water, structural damage, shingle damage, or burn masks.
2	*Minor damage*	Building partially burnt, water surrounding the structure, volcanic flow nearby, roof elements missing, or visible cracks.
3	*Major damage*	Partial wall or roof collapse, encroaching volcanic flow, or the structure is surrounded by water or mud.
4	*Destroyed*	Structure is scorched, completely collapsed, partially or completely covered with water or mud, or no longer present.

The xBD dataset was divided into 9,162 training images, 906 test images and 906 validation images,

[1] https://github.com/ddantas-ufs/2024_building

for a total of 10,974 images. This division ensures effective learning, evaluation and validation of the model, avoiding overfitting and improving generalization.

3.2 Data Preparation

The data preparation step plays a crucial role in building robust image segmentation models, allowing the model to capture the diversity of the input images and minimize the risk of overfitting. The image and mask are cropped to a specific size (512×512 pixels). After cropping, we use three approaches to prepare the data input:

1. Stacked images: concatenate two RGB input images into a single one with six channels, three channels from each input image.
2. Separated images: passing pre and post-disaster images separately to feed a Siamese network.
3. Difference between images: the difference between the two input images, forming a single input image with three channels corresponding to the intensity difference between the images.

3.3 Models Training

In the model training step, four neural network models, available in the Python libraries `segmentation_models` and `Pytorch`, were tested: UNet, FPN, Linknet, and PSPNet. Each of these models was implemented using seven backbones: BDANet, VGG16, ResNet18, ResNet50, ResNet34, ResNeXt50, and SENet154. A total of 28 combinations were trained. All of these models were trained using pre-trained weights from ImageNet.

For training the models, the Dice loss function was used, which is a commonly used metric to evaluate the overlap between the predicted mask and the groundtruth mask. We also used the focal loss function, which aims to solve the class unbalance problem.

Additionally, a weight was applied to the loss function to deal with class unbalance. These weights were set based on the frequency of the classes in the training images. The optimizer used was AdamW with a learning rate of 10^{-4} and a weight decay of 10^{-6}. The metric used to evaluate the model was the F1-score.

In each epoch of the training, the model receives every image of the training set. Transformations are randomly applied to each image to increase the variability of the data. Increasing the variability of the data allows the model to generalize better to new and unknown data. The following transformations were applied.

1. Horizontal mirroring: mirrors the image along the vertical axis.
2. Vertical mirroring: mirrors the image along the horizontal axis.
3. Rotation: rotates the image by a random angle between -10 and 10 degrees.
4. Scale: applies a random scale to the image between 0.8 and 1.2.
5. Additive gaussian noise: adds Gaussian noise to the image with a random scale between 0 and 0.05.
6. Contrast normalization: adjusts the contrast of the image to a random value between 0.8 and 1.2.
7. Elastic transformation: applies an elastic deformation to the image.

To increase the amount of examples per class, the CutMix technique was implemented. This technique consists of selecting a random rectangular part, with a probability of 87%, from an image and replacing it with a corresponding part from another image, with the respective annotation masks adjusted similarly as shown in Figure 1.

3.4 Morphological Filters

The application of mathematical morphology operations was performed in order to improve the F1-score of the best segmentation model that was obtained in the training. The use of morphological layers was composed of tests considering the sizes of the structuring elements 3×3 pixels (SeSize) and the shapes of the structuring elements squares (SeShape).

We tested four traditional morphological operations: erosion, dilation, opening and closing. These layers were inserted immediately after the Unet model softmax layer with the BDANet backbone. This layer has an image of dimension 512×512×5, each one of five channels in this image predicted represents a segmentation label. The training was carried out with a set of all the training images and the convolutional layers frozen.

3.5 Model Evaluation

We used the F1-score metric to evaluate the performance of the segmentation models used in the pre and post-disaster image segmentation problem.

The F1-score is defined as the harmonic mean between precision and recall and can vary from 0 to 1,

(a) (b) (c)

Figure 1: Example of CutMix application, which is represented in the red rectangles, on images. a) image pre-disaster, b) image post-disaster and c) post-disaster plus mask image.

Table 2: Models results in test dataset (Top 5 F1-score).

Nº	Different approaches for registered images	Model	Backbone	F1-score overall
1	Separated images	Unet	BDANet	0.761
2	Stacked images	Linknet	ResNet18	0.433
3	Stacked images	Linknet	VGG16	0.401
4	Stacked images	Linknet	ResNet50	0.368
5	Difference between images	Linknet	ResNet50	0.203

with values closer to 1 indicating a model with better performance. To calculate the F1-score, the segmentation masks produced by the models were compared with the grountruth segmentation masks.

In addition, to visualize the model results, we plotted the predictions that the model provided to verify if the model was generating the masks properly.

4 RESULTS

4.1 Experiments

We ran 28 experiments to identify which models have a better F1-score. Table 2 shows the F1-score of the five best models for pre and post-disaster image segmentation. The models were evaluated using the F1-score with 25 epochs.

The Unet model with the BDANet backbone, which treated the separated images, performed the best, with an F1-score of 0.761. This result highlights the effectiveness of the separated image approach, suggesting that maintaining image individuality can retain critical features that may be lost in other approaches.

Furthermore, the F1-score obtained can also be attributed to the use of the BDANet backbone, since the model showed high F1-scores compared to other models tested. The BDANet was proposed by Shen

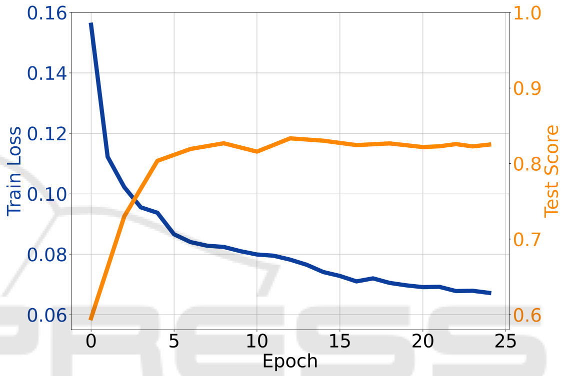

Figure 2: Train loss and test score by epochs of the best model.

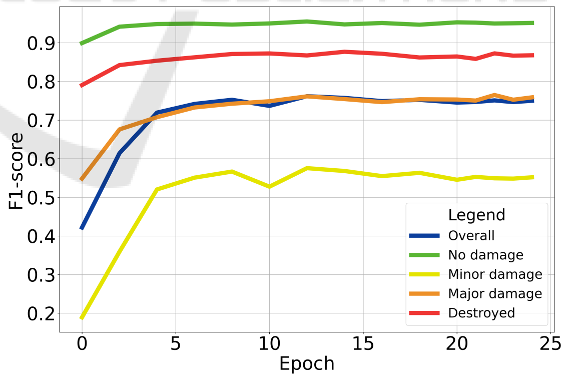

Figure 3: F1-score per class in each epoch of the best model.

and obtained an F1-score higher than other architectures in the damage segmentation task (Shen et al., 2021).

After the training step, the model with the highest F1-score was chosen to analyze the results and find opportunities to improve the F1-score. Figure 2 shows the train loss and test score over the training epochs.

The train loss is consistently decreasing over the

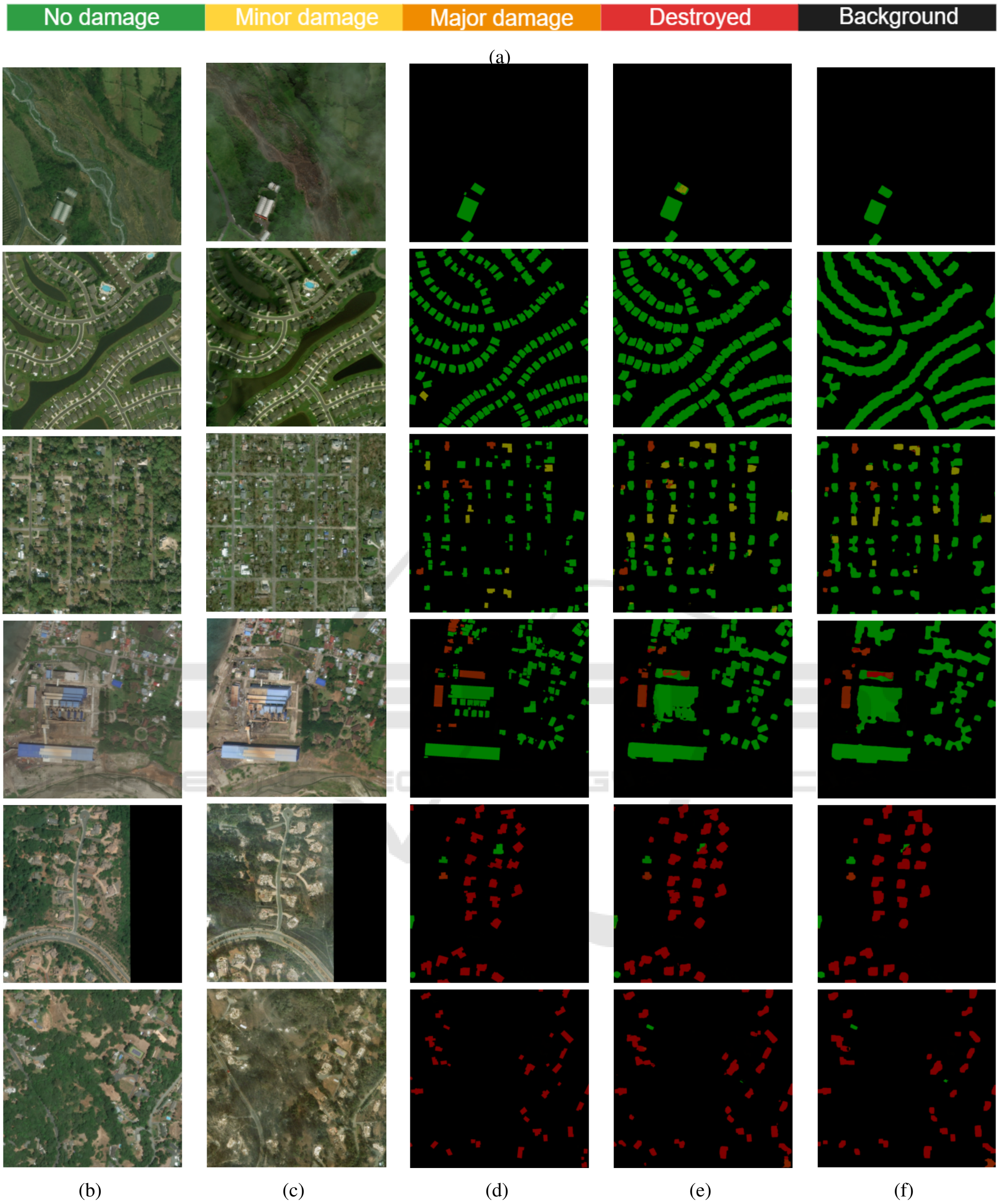

Figure 4: Best model prediction on an image example. a) Classes of masks, b) Image pre-disaster, c) Image post-disaster, d) Mask, e) Mask predicted and f) Mask predicted plus mathematical morphology.

epochs, suggesting that the model is continuously learning and improving. This is a positive sign that training is progressing as expected.

The test score was calculated as a weighted average of these two metrics: 0.3 times the Dice score plus 0.7 times the F1-score. The test score generally increases over time. This indicates that the performance of the model on the test set is improving.

In addition to analyzing the train loss and test score. Figure 3 shows the evolution of the F1-score

Table 3: Best model results after applying morphological layers.

Operation	F1-score	Increase F1-score
Dilation	0.799	0.038
Erosion	0.781	0.020
Closing	0.776	0.015
Opening	0.761	0.000

per class in each epoch of the best model.

The *overall* F1-score had an increasing trend in the test dataset, although there were some oscillations. This suggests that the model improved over the epochs.

We note that the *no damage* class consistently has the highest F1-score, suggesting that the model is more effective at predicting this class which represents the background.

In contrast, the *minor damage* and *major damage* classes have the lowest F1-scores, suggesting that the model has more difficulty predicting these classes or that it may have too few examples of these classes.

In addition to observing the trend by class of the *overall* F1-score over the epochs, visual results of the predictions were also evaluated, as shown in Figure 4.

Despite the model's F1-score having a satisfactory result, the model predictions had small errors in the completeness of the polygons. One of these errors can be clearly seen in the second row of Figure 4, where we have some predicted rectangles with small holes or inadequate fills.

From these observations, an experiment was carried out with the application of layers with mathematical morphology operations to improve the F1-score. Table 3 shows the best overall results with mathematical morphology experiments.

The last column of Table 3 shows the improvement in F1-score obtained with the addition of the morphological layers. When the morphology layer is applied after decision layer, there is an increase in the F1-score, leading to an improvement of 0.038 over the best model, reaching an F1-score of 0.799.

4.2 Comparison with Other Studies

Table 4, shows how the proposed model in this study compares to other models from related works.

The proposed model obtained an F1-score of 0.799. This model outperformed BDANet in the *no damage* and *destroyed* classes with an F1-score of 0.954 and 0.879 respectively. However, the proposed model underperformed in all other classes when compared to BDANet. We may try other techniques to improve the F1-score, such as ensemble methods, CutMix concentrated on the classes that had lower F1 scores or fine-tuning the hyperparameters with a grid search.

The FCN (Long et al., 2015; Shen et al., 2021), MTF (Weber and Kan, 2020), WNet (Hou et al., 2019; Shen et al., 2021) and Baseline model (Gupta et al., 2019) models achieved lower F1-scores than the proposed model and BDANet.

5 CONCLUSIONS

In this study, several models were evaluated regarding their F1-score in segmenting pre and post-disaster images.

The Unet model with the BDANet backbone obtained the best performance, achieving an F1-score of 0.761. This result indicates the effectiveness of the separated image approach, preserving their individual features that may be lost in other approaches.

BDANet may have contributed to the high performance of this model in extracting relevant features from images, as evidenced in the study by Shen (Shen et al., 2021).

The stacked image approach obtained inferior performance, with lower F1-scores than the other tested models. It was observed that the ResNet18 backbone architecture obtained a higher F1-score than VGG16 and ResNet50.

The results of these experiments indicate that applying layers with mathematical morphology operations can improve the F1-score of the model. The *overall* F1-score increased from 0.761 to 0.799.

When comparing the performance of the proposed model with other studies, it was observed that the proposed model outperformed the BDANet in the *no damage* and *destroyed* classes. In addition, the proposed model has higher F1-score in all classes compared to FCN, MTF, WNet and the baseline model.

However, the proposed model underperformed in all other classes when compared to BDANet, suggesting that there is still room for improving the F1-score.

Future works may include strategies to further improve the performance of the proposed model. The first one would be the implementation of an ensemble method. Secondly, we may apply CutMix concentrated on the classes that had lower F1-scores, such as the *minor damage* and *major damage* classes. Finally, fine tuning the hyperparameters with a grid search or random search could be an additional strategy to improve performance.

Table 4: Comparison of the F1-score among other studies. Table is in descending order by F1-score.

Models	*Overall*	*No damage*	*Minor damage*	*Major damage*	*Destroyed*
BDANet (Shen et al., 2021)	**0.806**	0.925	**0.616**	**0.788**	0.876
Proposed model	0.799	**0.954**	0.601	0.762	**0.879**
FCN (Long et al., 2015; Shen et al., 2021)	0.765	0.919	0.532	0.708	0.861
MTF (Weber and Kan, 2020)	0.741	0.906	0.493	0.722	0.837
WNet (Hou et al., 2019; Shen et al., 2021)	0.737	0.884	0.518	0.684	0.855
Baseline model (Gupta et al., 2019)	0.265	0.663	0.143	0.009	0.465

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