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Post-Earthquake Assessment of Building Damage using Deep Learning and Image Segmentation

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ABSTRACT: Building detection and damage assessment in satellite imagery are pivotal for effective disaster response and urban planning. The SegNet architecture, a deep convolutional neural network, has demonstrated significant potential in image segmentation tasks. However, accurately segmenting buildings and classifying their damage levels in satellite images remains challenging due to variations in building appearances and disaster-induced changes. This paper proposes a novel multiclass SegNet architecture for simultaneous segmentation of buildings and damage classification in pre- and post-disaster satellite imagery. Utilizing the xBD dataset, our model integrates pre-disaster building detection, post-disaster building detection, and damage classification into a unified framework. Evaluation metrics, including accuracy, Dice coefficient, and confusion matrices, demonstrate the model's robust performance, highlighting its potential for real-world disaster management applications.

KEYWORDS: SegNet, Building Segmentation, Damage Assessment, Satellite Imagery, Deep Learning, Disaster Response

I. INTRODUCTION

Earthquakes are one of the most devastating natural disasters, capable of causing widespread destruction to buildings, infrastructure, and essential services. Rapid and accurate assessment of earthquake-induced damage is paramount for effective emergency response, guiding search and rescue operations, allocating resources, and planning for recovery and reconstruction efforts. Traditional methods of damage assessment, which often involve manual ground surveys or visual inspection of aerial photographs, are frequently time-consuming, hazardous in affected areas, and can be overwhelmed by the scale of damage in major seismic events.

The availability of satellite imagery captured before and immediately after an earthquake provides a crucial resource for conducting large-scale damage assessments remotely. By comparing pre- and post-event images, changes indicative of structural damage, such as collapsed buildings, damaged roads, and debris accumulation, can be identified. However, the complexity and variability of earthquake damage patterns, coupled with challenges like cloud cover, image resolution, and the need for rapid analysis over vast areas, necessitate advanced automated techniques.

Deep learning techniques, particularly those focused on computer vision tasks like semantic segmentation, offer powerful capabilities for analyzing complex imagery and extracting detailed information at the pixel level. Semantic segmentation models can be trained to differentiate between various classes of damage (e.g., no damage, minor damage, major damage, destroyed) or to identify damaged structures directly from satellite images. Encoder-decoder architectures, such as SegNet, have proven effective in image segmentation tasks by capturing both high-level contextual information and fine-grained spatial details, making them suitable for the nuanced task of damage mapping from satellite imagery.

This article presents a deep learning framework employing a SegNet architecture specifically tailored for automated earthquake damage assessment using paired pre- and post-event satellite images. Our approach aims to leverage the comparative analysis of these image pairs to accurately detect and delineate earthquake-related damage. We utilize a relevant dataset containing satellite imagery from earthquake-affected regions to train and evaluate our model.

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II. LITERATURE SURVEY

Post-earthquake building damage segmentation has emerged as a vital research area due to the growing need for rapid and automated disaster response. Deep learning, especially encoder-decoder architectures such as SegNet and other customized convolutional networks, has significantly improved the accuracy and efficiency of segmentation tasks in this domain. This literature review aims to summarize key findings and methodologies from relevant studies in this field.

Badrinarayanan et al. (2017) [1] introduced SegNet, a deep convolutional encoder-decoder network specifically designed for pixel-wise image segmentation. SegNet leverages pooling indices from the encoder during the decoding process to improve spatial accuracy while reducing memory usage. Its ability to deliver precise segmentation results with lower computational requirements has made it a popular choice for real-time applications, including damage detection in satellite imagery.

Gupta et al. (2019) [2] utilized the xView2 dataset to develop deep learning models for automated building damage classification after natural disasters. Their work focused on identifying varying levels of damage using RGB satellite images and highlighted the importance of pre- and post-disaster imagery alignment, data augmentation, and multi-class segmentation for improved results in real-world scenarios.

Doshi et al. (2020) [3] proposed an ensemble-based framework that incorporated models like SegNet for accurate segmentation of damaged buildings. Their methodology included the integration of auxiliary data and post-processing techniques to enhance damage class differentiation, especially between structurally intact and severely destroyed buildings.

Cai et al. (2021) [4] introduced a Dual-Path CNN architecture for post-disaster building segmentation. Though inspired by multi-stage learning strategies, their model operates independently of U-Net and employs two consecutive encoder-decoder networks to progressively refine predictions. The first stage performs initial segmentation, while the second stage improves boundary accuracy and class separation. This dual-path approach was shown to increase accuracy across all damage severity levels.

Weber et al. (2020) [5] explored the integration of temporal satellite image pairs (before and after disaster) for damage classification using deep CNN architectures. Their findings emphasized the importance of temporal context and multi-view information in improving the detection of subtle structural changes.

Ronneberger et al. (2015) [6] introduced U-Net, a related encoder-decoder architecture widely used in medical and remote sensing applications. Their work inspired adaptations like SegNet for precise segmentation tasks in complex imagery.
Chen et al. (2021) [7] conducted a survey on deep learning for disaster damage assessment, emphasizing the need for integrated models that handle both building detection and damage classification. Our proposed method aligns with this need by using a single SegNet model for both tasks.

In conclusion, the literature demonstrates that SegNet and other custom deep learning models offer effective solutions for automated building damage segmentation. These architectures overcome key challenges such as class imbalance, complex urban features, and limited training data, thus playing a crucial role in developing reliable post-disaster assessment tools.

III. PROPOSED METHODOLOGY

The SegNet architecture is a convolutional neural network designed for pixel-wise segmentation, featuring an encoder path to extract features and a symmetric decoder path for precise localization. Our proposed multiclass SegNet model adapts this architecture to process pre- and post-disaster satellite images, producing three outputs: pre-disaster building masks, post-disaster building masks, and damage classification masks. Figure 1 illustrates the proposed methodology.
The proposed methodology for post-earthquake building damage assessment utilizes a deep learning approach based on a SegNet architecture to analyze paired pre- and post-event satellite imagery. The overall process involves dataset preparation, model architecture design, and a training and evaluation pipeline.

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A. Dataset Preparation

The study utilizes a dataset containing pre- and post-event satellite images, along with corresponding ground truth masks for pre-event buildings and damage levels. The dataset is organized into directories for pre-event images, post-event images, pre-event masks, and damage masks. A custom PyTorch Dataset class, xBD, is implemented to handle data loading and preprocessing.

Within the xBD dataset class, image and mask file paths are listed and sorted to ensure correct pairing. Images and masks are read into NumPy arrays. Several preprocessing steps are applied:

- Handling potential NaN values in images by converting them to zeros.
- Converting mask data types to float.
- Normalizing image pixel values to the range [0, 1] by dividing by 255.
- Adjusting damage mask values to represent specific damage classes (e.g., 0, 1, 2, 3, 4), with an ignore index (-1) for areas not considered for damage assessment.
- Optional data augmentation transformations can be applied.
- NumPy arrays are converted to PyTorch tensors, and the channel dimension is rearranged from (HWC) to (CHW).
- A post-event building mask is derived from the pre-event mask and the damage mask.

The loaded dataset is split into training, validation, and test sets. In this project, the data is split with 70% for training, 15% for validation, and 15% for testing. Data Loaders are created for each set to manage data batching during training and evaluation.

B. Model Architecture

The core segmentation model is a modified SegNet architecture, implemented as a SegNet class. This network consists of repeated DoubleConv blocks in both the encoder and decoder paths. Each DoubleConv block contains two convolutional layers, followed by batch normalization and ReLU activation. The encoder downsamples the input using max pooling, while the decoder upsamples using transposed convolutions and incorporates skip connections from the encoder to preserve spatial information. A bottleneck layer connects the encoder and decoder. The final layer of the SegNet is a 1x1 convolution.

For damage assessment from pre- and post-event images, a Dual_SegNet model is designed. This model utilizes two SegNet instances, one for processing the pre-event image and one for the post-event image. The outputs from these two SegNet branches are concatenated and then passed through a damage_head module. The damage_head consists of convolutional layers, batch normalization, and ReLU activations, ultimately predicting the damage class for each pixel. The entire Dual_SegNet model is moved to the appropriate computing device (GPU).

C. Training and Evaluation

The model is trained using CrossEntropyLoss as the criterion, ignoring pixels with a specified index (-1) in the ground truth masks. The Adam optimizer is used for updating the model's parameters with a learning rate of 0.001.

The training process involves iterating over the training DataLoader for a set number of epochs. In each training iteration, pre- and post-event image batches and their corresponding masks are fed into the Dual_SegNet model. The loss is calculated based on the model's output and the ground truth masks. The optimizer performs backpropagation and updates the model weights. The average training loss is tracked per epoch.

Model performance is evaluated on the validation set after each training epoch. During validation, the model is set to evaluation mode (model.eval()), and predictions are made without gradient calculation. The validation loss is calculated. Segmentation metrics, including Accuracy, Precision, Recall, and F1 Score, are computed based on the predicted damage masks and ground truth masks, considering the ignore index. A confusion matrix is also generated to provide a detailed breakdown of the model's classification performance per class. The average validation loss and computed metrics are reported.

After training, the model is evaluated on the unseen test set using the same metrics and procedure as the validation phase. The final test set evaluation results are reported.

The trained model's state dictionary can be saved and loaded for future use or inference [1]. Additionally, the training and validation losses can be plotted over epochs to visualize the learning curve [2]. The methodology also includes code to

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process full images by splitting them into patches for prediction and then reconstructing the full predicted damage maps . Visualizations of predicted masks on test cases are generated .

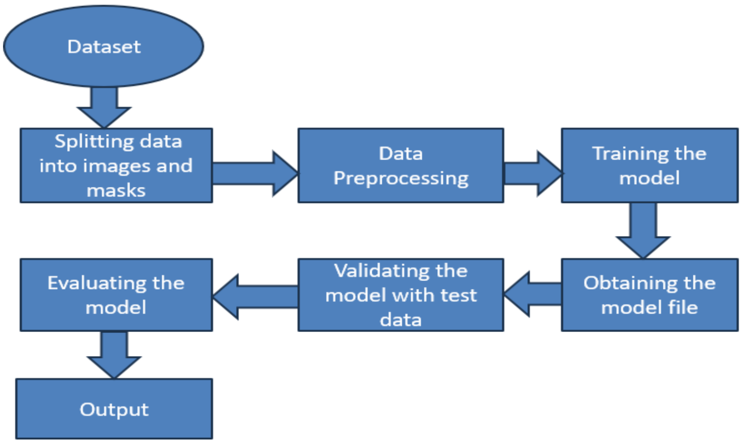

Figure 1: Block diagram for proposed methodology

IV. TESTING AND RESULTS

The proposed SegNet model was trained and evaluated to assess its performance in post-earthquake building damage assessment. The dataset was partitioned into training, validation, and test sets for experimentation. The model was trained using the Adam optimizer and CrossEntropyLoss.

During the training process, the model's performance was monitored by tracking the average training and validation losses per epoch. After one epoch of training, the average training loss was recorded as 0.8449, and the average validation loss was 0.9415.

The learning curve, showing the training and validation loss over the epochs, is illustrated in Figure 2.

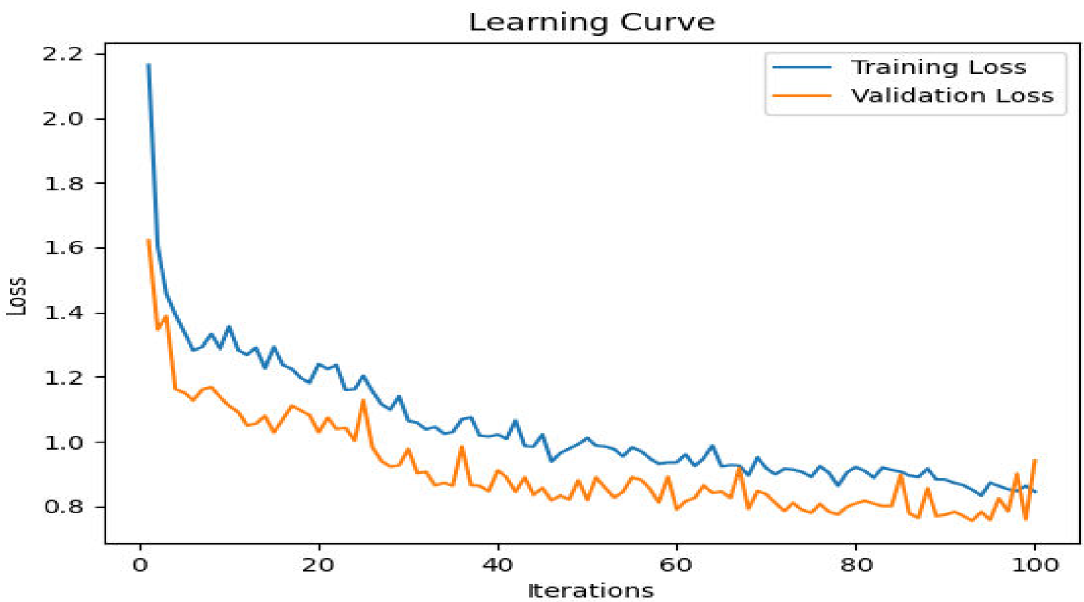

Figure 2: Epochs vs Loss

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The Confusion matrix on the test dataset is showed on the Figure 3.

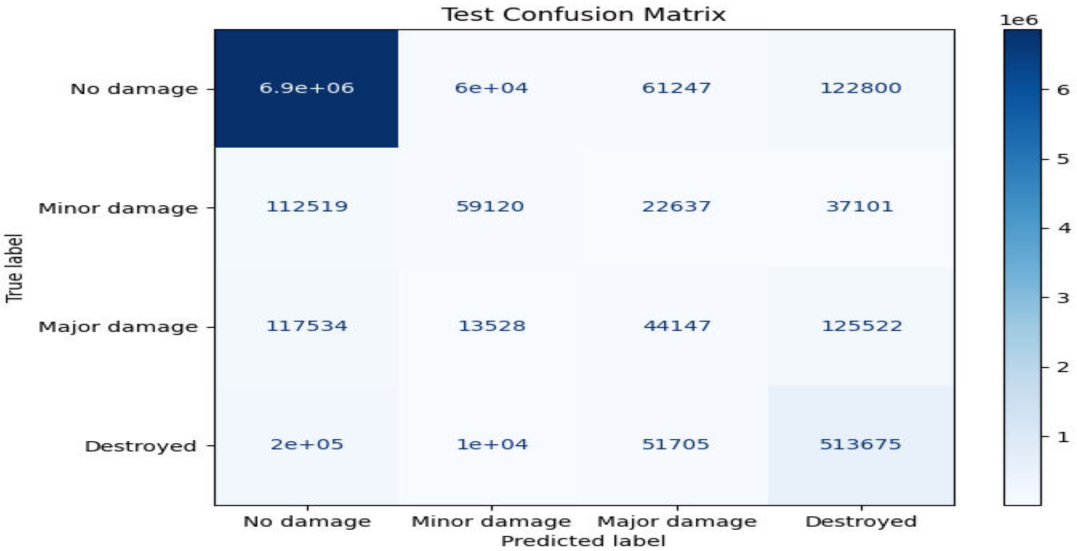

Figure 3. Confusion Matrix

In addition to quantitative metrics, the model's performance was qualitatively assessed through the visualization of predictions on test images. Figure 4 shows examples of the input pre- and post-event images, and the corresponding predicted damage masks. These visualizations were generated by processing large images by dividing them into smaller patches, generating damage predictions for each patch using the trained model, and then reconstructing the full predicted damage maps. These visual results demonstrate the model's ability to produce segmentation masks indicating damaged areas in post-earthquake satellite imagery and provide a visual confirmation of the model's output.

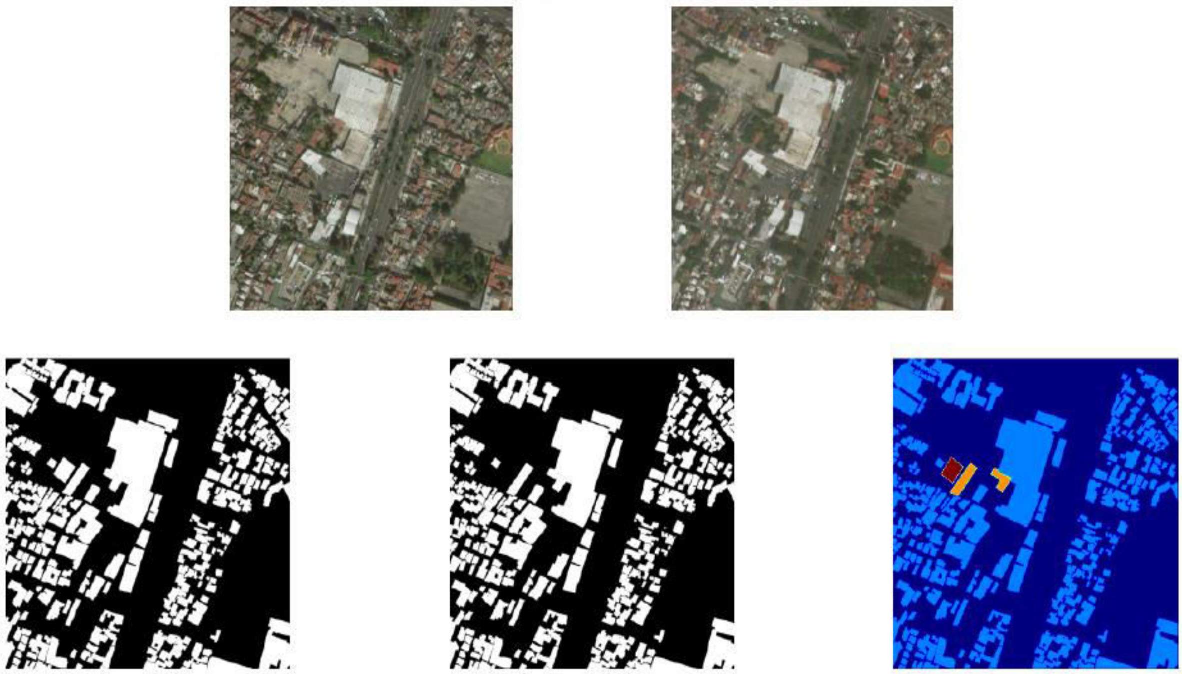

Figure 4: Original Pre-Disaster Image, Original Post-Disaster Image, Pre-Building Mask, Post-Building Mask, Damage Mask.

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V. CONCLUSION

Based on the results presented, the proposed SegNet methodology demonstrates potential for automated earthquake damage assessment using pre- and post-event satellite imagery. The model was successfully trained and evaluated, providing quantitative metrics on its performance in identifying damaged buildings.The validation and test results indicate the model's capability in segmenting damage classes, although the performance metrics suggest that there is room for improvement, particularly in achieving higher precision and recall across all damage categories. The visual results from the test predictions illustrate the model's ability to generate damage maps from unseen satellite images, which is a critical step towards automating post-earthquake damage assessment.

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