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AUTOMATED BUILDING DAMAGE ASSESSMENT USING FEATURE-CONCATENATED SIAMESE NEURAL NETWORKS

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ABSTRACT

Building damage assessment is a crucial task in post-disaster management, enabling rapid response and resource allocation. Traditional methods relying on field surveys and manual remote sensing analysis are time-consuming, costly, and often impractical in disaster-stricken areas. To address these limitations, this research proposes an advanced approach utilizing a **Feature-Concatenated Siamese Neural Network (FCSNN)** for automated building damage classification. The model leverages pre-earthquake and post-earthquake data, implementing a novel concatenation mechanism that enriches feature extraction by aggregating low-, mid-, and high-level representations. This enhancement enables improved discrimination of structural changes, significantly boosting classification performance.

Our study conducts three experimental scenarios: (1) binary classification of intact (G1) vs. collapsed (G5) buildings, (2) classification of non-collapsed (G1-G4) vs. collapsed (G5) buildings, and (3) multi-class classification based on the five **EMS-98** building damage grades. The proposed FCSNN model achieves **F1-scores of 79.47%, 54.09%, and 40.64%** for the respective experiments, outperforming conventional Siamese Neural Networks (SNN) and state-of-the-art Support Vector Machine (SVM)-based methods. The model also attains **accuracy scores of 87.24%, 95.28%, and 42.57%** across the three scenarios, demonstrating its robustness in handling imbalanced datasets and complex damage patterns.

The findings validate the effectiveness of feature concatenation in deep learning-based damage assessment, offering an efficient and scalable solution for post-disaster building evaluation. Future enhancements include the integration of **voxel-based representations** and alternative sub-network architectures to further refine classification accuracy. This study contributes to the advancement of AI-driven disaster response frameworks, facilitating **faster and more reliable damage assessments** in real-world scenarios.

Keywords: Building Damage Assessment, Feature-Concatenated Siamese Neural Network, Deep Learning, Post-Disaster Classification, Remote Sensing, LiDAR, EMS-98.

INTRODUCTION

BUILDINGS are an essential aspect of the life of every human being. Most people live and work in buildings. However, buildings are very vulnerable to natural disasters. An earthquake, for example, is known to very often cause damage to buildings and even take lives [1]. Most of the injuries and casualties are caused by falling debris from the building [2], [3]. Therefore, it is important for the rescue team to immediately observe the condition of the building after the earthquake to assist the disaster response process and rescue operations [4], [5]. Previously, the post-earthquake observation process was carried out by conducting field surveys, which

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were timeconsuming, costly, and terrible for creating building damage maps and planning rescue operations. Moreover, in some cases, this is not possible to do due to broken or blocked roads caused by the earthquake making some locations impossible to be accessed [1], [6]–[8]. Especially, for extensively devastated areas, getting the results right away after the disaster is no longer feasible [9]. Alternatively, Remote sensing and geographical information system (GIS) technology can beapplied to accelerate this VOLUME 11, 2023 work as it can capture affected areas from space [10], [11]. However, doing manual observations using remote sensing and GIStechnology still takes a lot of time if the area affected by the disaster is wide [12]. Therefore, the post-earthquake building observation process needs to be automated. Previous researches [1], [13] utilize artificial intelligence based on satellite imagery to automate post-earthquake building observation. However, there are certain types of collapsed patterns that cannot be captured using images, one of which is pancake collapse where the building collapsed vertically with an intact rooftop [14]. light detection and ranging (LiDAR) point cloud data can be used to address this problem since it has height information. Previous researches that based on LiDAR data [5], [6] use support vector machine (SVM) with a handcrafted feature that is not robust and requires human expertise. Therefore this research utilizes a Siamese neural network that has a convolutional neural network (CNN) as its sub-network to automatically perform feature extraction. Fujita [15] use an unshared weight siamese neural network (SNN) to detect tsunami-whased buildings because the appearance of the pretsunami and the post-tsunami image is dissimilar. However, in the case of an earthquake, the appearance of the preearthquake and post-earthquake building is not as dissimilar as tsunami-washed, since the building is either damaged or collapsed instead of washed away. This research decided to keep the weight sharing since the idea is to perform classification based on the change after the disaster occurred. Moreover, the weight sharing makes our model very analogous to previous researches that use LiDAR on earthquake data. As of what has been found by [5] that the difference between pre-earthquake feature and post-earthquake feature is the most informative feature, therefore we apply some modification to the SNN to enrich this feature. We perform three experimentalscenarios, oneofwhichisafive-classclassification using all five Grades of EMS-98 building damage description to further detail the post-earthquake observation. Asfar as the author is concerned, this research is the only one that classifies building damage in the Kumamoto Prefecture earthquake that used all five Grades of EMS-98 based on LiDAR data.

2. PROBLEM STATEMENT

Natural disasters such as earthquakes, floods, hurricanes, and explosions often cause severe damage to buildings and infrastructure. Rapid and accurate assessment of building damage is crucial for emergency response, rescue operations, and reconstruction planning. Traditional building damage assessment methods rely heavily on **manual inspection by experts**, which is time-consuming, costly, and sometimes unsafe, especially in disaster-affected areas.

With the availability of **satellite and aerial imagery**, automated damage assessment techniques have been explored. However, many existing systems struggle to accurately compare **pre-disaster and post-disaster images** due to variations in lighting, angle, and environmental conditions.

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Conventional image processing techniques often fail to capture complex structural changes in buildings.

Therefore, there is a need for an **intelligent automated system** that can effectively analyze image pairs and accurately identify building damage. The use of **feature-concatenated Siamese Neural Networks** can improve damage detection by learning meaningful representations from both pre-event and post-event images, enabling reliable and faster building damage assessment.

3.OBJECTIVES

1. **To develop an automated system** for detecting and assessing building damage using deep learning techniques.
2. **To utilize Siamese Neural Networks** for comparing pre-disaster and post-disaster building images.
3. **To implement feature concatenation techniques** that enhance feature representation and improve classification accuracy.
4. **To accurately identify and classify building damage levels** from aerial or satellite images.
5. **To reduce the time and effort required for manual damage assessment** during disaster management.
6. **To improve disaster response and recovery planning** by providing reliable damage analysis.
7. **To design a scalable system** that can be applied to large-scale disaster-affected areas using remote sensing data.

4.LITERATURE REVIEW

Building damage assessment after disasters such as earthquakes, floods, and hurricanes is essential for rapid rescue operations and infrastructure recovery. Traditional manual inspection methods are time-consuming and risky, which has encouraged the use of **remote sensing imagery and deep learning techniques** for automated damage detection. Recent research focuses on **deep neural networks, change detection models, and Siamese architectures** to analyze pre- and post-disaster images and determine the level of structural damage.

Deep Learning for Building Damage Detection

Early research explored the use of **convolutional neural networks (CNNs)** to detect damaged buildings from satellite or aerial imagery. CNN models automatically learn spatial features from images and classify buildings based on damage severity. Studies have shown that deep learning models significantly improve accuracy and reduce the need for manual feature engineering in disaster assessment tasks.

Researchers also developed **object-based semantic change detection frameworks**, where pre- and post-disaster images are compared to identify structural changes. These systems integrate building localization networks with damage classification models to produce faster and more accurate disaster assessments across large geographic areas.

Siamese Neural Networks for Change Detection

Siamese neural networks are widely used for **image similarity comparison and change detection tasks**. A Siamese architecture consists of two identical neural networks sharing the same parameters, which process two input images simultaneously and compare their extracted features.

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In building damage assessment, Siamese networks analyze **pre-disaster and post-disaster satellite images** to detect structural differences. Research shows that Siamese-based models can effectively learn feature representations and identify damage patterns in remote sensing imagery.

Several studies introduced **Siamese U-Net and fully convolutional Siamese networks**, where one branch processes pre-disaster images and the other processes post-disaster images. These architectures enable accurate detection of damaged buildings and improve classification performance by capturing spatial and temporal differences between images.

Feature Fusion and Concatenation Techniques

Recent research highlights the importance of **feature fusion techniques** for improving damage detection accuracy. Feature concatenation combines outputs from different convolutional layers or network branches to create richer feature representations.

A proposed **feature-concatenated Siamese neural network** enhances the feature extraction capability by merging multiple convolutional outputs into a high-dimensional feature vector. This approach improves the model's ability to distinguish between different levels of structural damage and achieves higher classification accuracy compared with traditional Siamese networks.

Experimental results from this model demonstrated improved performance in classifying building damage levels using disaster datasets, showing better accuracy and F1-scores than standard Siamese architectures.

Advanced Deep Learning Architectures

To further improve accuracy, researchers have explored **transformer-based and multi-scale neural networks** for building damage assessment. For example, hierarchical transformer architectures and attention-based networks enhance feature extraction and capture long-range spatial relationships in high-resolution satellite imagery.

These advanced models combine **multi-scale feature learning, attention mechanisms, and Siamese architectures** to better analyze large-scale disaster imagery datasets such as the xBD dataset.

Research Gap

Despite significant progress, existing approaches still face challenges such as:

- Difficulty detecting **small or partially damaged buildings**.
- Limited ability to generalize across **different disaster types and geographic regions**.
- High computational requirements for processing large satellite datasets.

Therefore, integrating **feature concatenation with Siamese neural networks** provides a promising solution by improving feature representation, enhancing classification accuracy, and enabling more efficient automated building damage assessment.

5.SYSTEM ANALYSIS

Existing System

Overview of Traditional Building Damage Assessment

Post-earthquake building damage assessment has traditionally relied on **manual field surveys** and **satellite imagery analysis**. While these methods have been effective in certain scenarios, they are

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time-consuming, expensive, and impractical for large-scale disaster events. Manual field surveys require trained experts to assess structural damage, which may not be feasible in regions with extensive devastation or inaccessible locations due to infrastructure collapse.

To address these limitations, researchers have increasingly explored **remote sensing and artificial intelligence (AI)-based techniques** to automate damage classification. The existing automated damage assessment approaches can be broadly categorized into **image-based methods, LiDAR-based methods, and machine learning-based classification models**.

Image-Based Damage Assessment

Use of Satellite and Aerial Imagery

Many existing studies utilize **pre-earthquake and post-earthquake satellite or aerial images** to detect damaged buildings. These methods typically involve **image segmentation, feature extraction, and deep learning-based classification**.

For instance, **Ji et al. (2019)** used **CNN-based feature extraction** on satellite images to classify collapsed buildings in the **2010 Haiti earthquake**, achieving **87% accuracy [1]**. Similarly, **Miura et al. (2020)** applied deep learning to aerial images from the **2016 Kumamoto and 1995 Kobe earthquakes**, reporting **93% accuracy [2]**.

Limitations of Image-Based Methods

- **Inability to Capture Structural Deformations**: Image-based models primarily assess **surface-level** damage and struggle to detect **pancake collapses**, where a building collapses vertically with an intact rooftop.
- **Occlusions and Shadows**: Buildings in dense urban areas may be **partially obscured**, reducing classification accuracy.
- **Lack of Height Information**: Satellite images lack **3D structural details**, making it difficult to assess partial collapses or subtle damage patterns.

LiDAR-Based Damage Assessment

LiDAR for Height-Based Damage Detection

To overcome the limitations of image-based methods, researchers have explored **LiDAR (Light Detection and Ranging) technology**, which captures **3D structural information** of buildings.

- **Moya et al. (2018)** applied **LiDAR-based height difference analysis** for the 2016 Kumamoto earthquake, achieving **93% accuracy** using an **SVM classifier [3]**.
- **Hajeb et al. (2020)** used **GLCM feature extraction** and **SVM classification** on LiDAR-derived **Digital Surface Models (DSMs)**, reporting **87% accuracy [4]**.

Limitations of LiDAR-Based Methods

- **Computational Complexity**: Processing raw LiDAR point clouds requires significant computational resources.
- **Handcrafted Feature Dependency**: Existing LiDAR-based models rely on **manual feature engineering**, which may not generalize well across different earthquake datasets.
- **Limited Data Availability**: LiDAR datasets are less frequently available than satellite imagery, restricting real-world applications.

Machine Learning and Deep Learning Approaches

Early Machine Learning Models

Before deep learning, **Support Vector Machines (SVMs)** and **Random Forest (RF)** classifiers were widely used for damage classification.

- **Moya et al. (2018)** and **Hajeb et al. (2020)** employed **SVMs** for LiDAR-based damage classification. However, their reliance on **manually crafted features** limited their scalability **[3,4]**.
- **Fujita et al. (2017)** introduced a **pseudo-Siamese Neural Network (SNN)** for tsunami-damaged building detection, but

the model was not optimized for earthquake-induced collapses **[5]**.

Conventional Siamese Neural Networks (SNNs)

Siamese Neural Networks (SNNs) have gained attention for **change detection tasks**. An **SNN consists of two identical sub-networks** that process pre- and post-disaster data and compute differences for classification.

- **Fujita et al. (2017)** applied an **unshared-weight SNN** for tsunami-damaged buildings, achieving moderate success in change detection **[5]**.
- While SNNs automate **feature extraction**, they often lack **multi-level feature representation**, limiting their classification accuracy.

Limitations of Existing Deep Learning Models

- **Lack of Multi-Level Feature Extraction**: Traditional SNNs primarily utilize high-level features, losing important **low- and mid-level** structural information.
- **Challenges in Capturing Partial Collapses**: Standard SNNs may struggle with **subtle building deformations** due to their limited feature representation.

PROPOSED SYSTEM

Overview of Feature-Concatenated Siamese Neural Network (FCSNN)

To overcome the limitations of existing damage assessment methods, we propose a **Feature-Concatenated Siamese Neural Network (FCSNN)**, which enhances conventional **SNN architectures** by incorporating **multi-level feature aggregation**. This novel approach improves damage classification accuracy by **concatenating low-, mid-, and high-level feature representations**, thereby preserving structural details at multiple abstraction levels.

Key Features of the Proposed FCSNN Model

Multi-Level Feature Concatenation

- Unlike traditional SNNs, which only utilize **final-layer feature maps**, our **FCSNN aggregates features** from **all convolutional layers**.
- This **concatenation mechanism** improves the ability to **differentiate subtle damage patterns**, such as **partial collapses and internal structural deformations**.

Improved Change Detection Mechanism

- The model **extracts hierarchical feature maps** from both pre-earthquake and post-earthquake data.
- A **feature subtraction layer** computes the difference between corresponding features at **multiple levels**, enhancing damage classification accuracy.

Automatic Feature Learning

- Unlike **SVM-based models**, which require **manual feature selection**, FCSNN **learns features automatically** through its deep network architecture.
- This eliminates the need for **handcrafted features**, making the model more adaptable to **different earthquake scenarios**.

Robustness to Class Imbalance

- To address the **class imbalance issue**, the model incorporates **class weighting and dropout regularization**.
- This ensures **better generalization** and **reduces overfitting** to dominant classes.

Experimental Validation

To evaluate the effectiveness of our proposed **FCSNN model**, we conducted three experimental scenarios:

1. **Binary Classification: Intact (G1) vs. Collapsed (G5)**
   - Tests the model's ability to classify **completely collapsed vs. undamaged buildings**.

2. **Binary Classification: Non-Collapsed (G1-G4) vs. Collapsed (G5)**
   - Merges **Grades 1–4** into a **single non-collapsed class**, reflecting practical post-disaster scenarios.
3. **Multi-Class Classification: All Five EMS-98 Grades**
   - Evaluates the model's performance in **fine-grained damage classification** across all **five EMS-98 categories**.

Expected Contributions and Advantages

- **Higher Accuracy**: Outperforms traditional SNN and SVM models in **F1-score and accuracy**.
- **Scalability**: Suitable for **large-scale earthquake damage assessment** using LiDAR and remote sensing data.
- **Better Generalization**: Eliminates reliance on handcrafted features, making it adaptable to **various earthquake datasets**.

CONCLUSION

This research develops a classification model for building damage assessment based on pre-earthquake point cloud and post-earthquake point cloud. The problem we discussed in 16 We conducted three experiment scenarios where we outperformed our comparison models and achieved an F1 score of 79.47%,54.09%,and40.64%forexperimentI,experiment II, and experiment III respectively. In terms of accuracy, we achieved an accuracy score of 87.24%, 95.28%, and 42.57% for experiment I, experiment II, and experiment III respectively. Indeed, this result can still be improved by implementing certain approaches to improve the performance of this model. This research is an initial research on the FCSNN. Therefore, there are still many things that can be improved and further worked on in the future. For future work, we would like to consider the use of Voxel as areplacementforDSMtoimproveourresults.Wealsoplan to conduct some research related to this topic using different sub-network architectures for the FCSNN. The most important thing in this research is introducing a novel architecture based onanSNN.Wealsohaveaplantobringthismodelinto other fields such as sequence embedding and compare our result with Zheng et al's SENSE[38]. Thecombinationofour idea and SENSE also interests us. Another field that caught our interest is image analysis such as patch matchingbyHanif et al [39] which uses enhanced two-channel and SNN on the UBCimagepatch benchmark dataset [40]. For now, we hope this research can be useful as a foundation for future research.

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