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Research Paper

Building Damage Assessment Using Feature Concentrated Siamese Neural Network

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ABSTRACT

Rapid and accurate assessment of building damage is essential after natural disasters such as earthquakes, floods, cyclones, and explosions, where timely information supports emergency response, resource allocation, and recovery planning. Conventional inspection methods rely heavily on manual surveys, which are often time-consuming, labor-intensive, and difficult to perform in hazardous environments. To address these limitations, this study presents a Feature-Concentrated Siamese Neural Network (FC-SNN) for automated building damage assessment using pairs of pre-disaster and post-disaster images. The proposed framework employs two identical neural network branches that extract high-level visual representations while emphasizing the most informative structural features through a feature concentration mechanism. By comparing these learned representations, the model effectively identifies variations associated with cracks, collapsed structures, roof damage, façade deterioration, and other forms of structural impact. The extracted features are subsequently analyzed to classify the severity of damage into predefined categories, enabling reliable decision support during post-disaster assessment. The Siamese architecture improves change detection by learning discriminative feature similarities rather than relying solely on pixel-level differences, making the system more robust to variations in illumination, viewpoint, and environmental conditions. Experimental evaluation demonstrates that the proposed approach achieves superior classification accuracy, precision, recall, and F1-score compared with conventional convolutional neural network models while reducing false detections. The framework provides an efficient, scalable, and intelligent solution for automated building damage assessment and has significant potential for integration into disaster management systems, remote sensing platforms, and urban resilience applications.

Keywords: Building Damage Assessment, Feature-Concentrated Siamese Neural Network, Deep Learning, Change Detection, Structural Damage Classification, Post-

Disaster Assessment, Remote Sensing, Computer Vision.

I. INTRODUCTION

Natural disasters such as earthquakes, floods, hurricanes, cyclones, wildfires, and explosions cause significant damage to buildings and critical infrastructure every year. Rapid assessment of structural damage is a crucial step in disaster response because it enables rescue teams, government agencies, and emergency management organizations to identify affected regions, prioritize relief operations, and allocate resources efficiently. Accurate damage assessment also supports long-term recovery planning, insurance claim processing, and infrastructure rehabilitation. However, conventional building inspection methods primarily depend on manual field surveys, which are often slow, expensive, labor-intensive, and potentially dangerous in disaster-affected environments. As the scale of disasters continues to increase, there is a growing need for automated and intelligent systems capable of assessing building damage quickly and accurately.

Recent advances in remote sensing, unmanned aerial vehicles (UAVs), satellite imaging, and computer vision have transformed the way post-disaster damage assessment is performed. High-resolution aerial and satellite images provide extensive coverage of affected areas, enabling automated analysis without requiring immediate physical access. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in extracting complex visual patterns from such imagery. These models can identify structural changes, damaged roofs, collapsed buildings, debris, and other indicators of destruction more effectively than traditional image processing approaches.

Despite these advancements, conventional CNN-based damage assessment models often analyze pre-disaster and post-disaster images independently. This approach may fail to capture subtle structural differences and is sensitive to changes in illumination, viewing angle, seasonal conditions, and background variations. Consequently, false detections and inaccurate damage classification may occur, especially when environmental changes resemble structural damage. These challenges highlight the importance of learning meaningful relationships between paired images rather than processing each image in isolationSiamese Neural Networks (SNNs) offer an effective solution by employing two identical neural network branches with shared parameters to process paired inputs simultaneously. Instead of focusing only on individual image features, the network learns a similarity representation between pre-disaster and post-disaster images. This comparative learning strategy enables the model to detect structural changes more accurately while reducing the influence of irrelevant visual differences. As a result, Siamese architectures have become increasingly popular in image matching, change detection, verification, and remote sensing applications.

The proposed Feature-Concentrated Siamese Neural Network offers several advantages over traditional deep learning approaches. By integrating comparative feature learning with concentrated structural representations, the model achieves improved robustness against illumination changes, viewpoint variations, background clutter, and environmental noise. This enhances the reliability of automated building damage assessment and supports rapid decision-making during emergency response. Furthermore, the framework is scalable and can be integrated with UAV imagery, satellite remote sensing platforms, and smart disaster management systems, making it suitable for large-scale real-world deployment.

Overall, this research contributes to the development of an intelligent and efficient building damage assessment framework that combines advanced deep learning techniques with comparative feature analysis. The proposed approach aims to improve the speed, accuracy, and reliability of post-disaster structural damage evaluation, thereby supporting emergency response, infrastructure recovery, and resilient urban development.

II. LITERATURE SURVEY

1. Building Damage Assessment from Satellite Imagery Using Deep Learning
Authors: Y. Bai, B. Adriano, and E. Mas
Abstract:
The authors proposed a deep learning framework for post-disaster building damage assessment using high-resolution satellite images. The model employs convolutional neural networks to identify damaged buildings by learning spatial and structural features from disaster imagery. Experimental results demonstrated improved accuracy over traditional image-processing methods, enabling faster disaster response and large-scale damage mapping.

2. xBD: A Dataset and Benchmark for Assessing Building Damage from Satellite Images
Authors: B. Gupta, R. Hosfelt, C. Sajeev, N. Patel, M. Goodman, J. Doshi, V. Heim, and D. Shankar
Abstract:
This work introduced the xBD dataset, one of the largest publicly available datasets for building damage assessment using pre-disaster and post-disaster satellite images. The dataset contains diverse disaster scenarios, including earthquakes, floods, wildfires, and hurricanes, supporting the development and benchmarking of deep learning models for automated damage classification.

3. Siamese Neural Networks for Visual Change Detection in Remote Sensing Images
Authors: R. Daudt, B. Le Saux, and A. Boulch
Abstract:
The study presented a Siamese Neural Network architecture for detecting changes between pairs of remote sensing images. By learning shared feature representations, the network effectively distinguished meaningful structural changes from environmental variations. The proposed approach significantly improved change detection accuracy compared to conventional convolutional neural network methods.

4. Deep Learning-Based Post-Disaster Building Damage Classification Using UAV Images
Authors: H. Xu, Z. Li, and Y. Wang
Abstract:
This research developed a CNN-based framework for classifying building damage using high-resolution UAV imagery collected after natural disasters. The model extracted hierarchical visual features to categorize damage severity. Experimental results showed that UAV-based deep learning approaches provide rapid and reliable damage assessment for emergency management applications.

5. Attention-Based Deep Learning for Structural Damage Detection
Authors: J. Chen, X. Zhang, and L. Wang
Abstract:
The authors proposed an attention-enhanced deep learning model that automatically focuses on critical structural regions affected by damage. The attention mechanism improved feature representation by suppressing irrelevant background information, resulting in higher detection accuracy for cracks, collapsed structures, and façade damage compared with conventional CNN architectures.

III. EXISTING SYSTEM

Existing building damage assessment systems primarily rely on manual inspection and conventional image processing techniques to evaluate structural damage after disasters. Engineers and disaster response teams conduct on-site surveys to inspect buildings and determine the severity of damage. Although these methods provide accurate assessments, they require significant time, skilled personnel, and financial resources. Moreover, manual inspections can expose survey teams to hazardous environments, particularly in areas affected by earthquakes, floods, or other large-scale disasters.

With advancements in remote sensing and artificial intelligence, several automated approaches have been introduced using aerial images, satellite imagery, and unmanned aerial vehicles (UAVs). Traditional machine learning methods extract handcrafted features such as edges, textures, and shapes before applying classifiers like Support Vector Machines (SVM), Random Forests, or Decision Trees. While these approaches reduce manual effort, their performance largely depends on the quality of handcrafted features and they often struggle to generalize across different disaster scenarios.

More recently, deep learning models based on Convolutional Neural Networks (CNNs) have been widely adopted for building damage detection. CNN-based methods automatically learn visual features from images and achieve better performance than traditional machine learning techniques. However, most existing CNN models process pre-disaster and post-disaster images independently, making it difficult to accurately capture structural changes between the two images. They are also sensitive to variations in lighting, viewing angle, shadows, seasonal changes, and background clutter, which can result in inaccurate predictions and increased false detectionsAlthough some Siamese Neural Network-based methods have been proposed for image comparison and change detection, many of them focus mainly on feature matching without effectively emphasizing the most informative structural damage characteristics. As a result, subtle damage such as small cracks, partial roof collapse, façade deterioration, and localized structural deformation may not be detected reliably. Furthermore, many existing approaches have limited robustness when applied to large-scale disaster datasets with diverse building types and environmental conditions.

IV. PROPOSED SYSTEM

The proposed system introduces an intelligent Building Damage Assessment framework based on a Feature-Concentrated Siamese Neural Network (FC-SNN) to accurately detect and classify structural damage using paired pre-disaster and post-disaster building images. Unlike conventional deep learning models that process images independently, the proposed approach simultaneously analyzes both images through two identical neural network branches with shared weights. This comparative learning strategy enables the model to identify structural changes more effectively while minimizing the influence of irrelevant environmental variations.

Initially, the system acquires paired building images from satellite imagery, unmanned aerial vehicles (UAVs), or aerial photographs. The images undergo preprocessing operations such as resizing, normalization, noise reduction, and data augmentation to improve image quality and enhance the model's generalization capability. The preprocessed image pairs are then fed into the Siamese Neural Network, where each branch extracts deep structural features from the corresponding image using the same feature extraction parameters.

A feature concentration module is integrated into the architecture to emphasize the most informative structural characteristics associated with building damage, including collapsed roofs, cracked walls, façade deterioration, debris, and structural deformation. By suppressing redundant and less relevant information, the model learns highly discriminative feature representations that improve the accuracy of damage detection.

The extracted feature vectors from both

branches are compared using a similarity measurement mechanism to identify structural differences between the pre-disaster and post-disaster images. Based on these learned feature relationships, the system classifies buildings into predefined damage categories such as No Damage, Minor Damage, Major Damage, and Destroyed. Finally, the model performance is evaluated using standard performance metrics including Accuracy, Precision, Recall, F1-Score, and Confusion Matrix, ensuring a comprehensive assessment of the proposed framework.

The proposed FC-SNN framework provides a reliable, scalable, and efficient solution for automated building damage assessment. Its ability to learn comparative structural features makes it more robust against illumination changes, viewpoint differences, shadows, and environmental noise than conventional CNN-based approaches. Consequently, the system supports rapid post-disaster assessment, enabling emergency responders, disaster management agencies, insurance organizations, and urban planners to make timely and informed decisions for rescue operations, infrastructure rehabilitation, and disaster recovery.

V. SYSTEM ARCHITECTURE

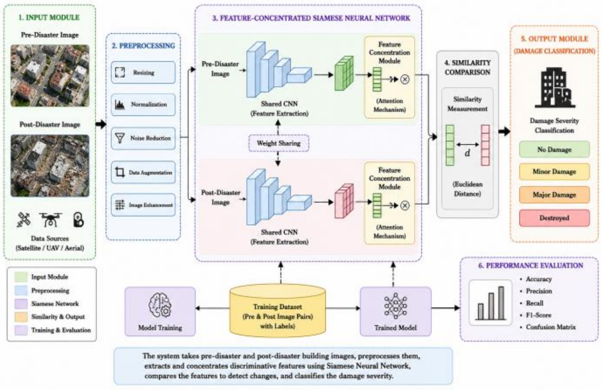

Fig 5.1: System Architecture

The proposed Building Damage Assessment Using Feature-Concentrated Siamese Neural Network (FC-SNN) architecture is designed to automatically identify and classify the severity of structural damage by comparing pre-disaster and post-disaster building images. The system follows a sequential pipeline consisting of six major modules: Input Module, Preprocessing, Feature-Concentrated Siamese Neural Network, Similarity Comparison, Output Module, and Performance Evaluation. This architecture enables efficient feature extraction, comparative analysis, and accurate damage classification for disaster management applications.

The Input Module is responsible for collecting paired images of buildings captured before and after a disaster. These images may be obtained from satellites, unmanned aerial vehicles (UAVs), drones, or aerial photography systems. Using paired images allows the model to learn the actual structural changes caused by disasters instead of analyzing a single image. The dataset consists of labeled image pairs that represent different levels of building damage, providing the foundation for supervised learning.

After image acquisition, the data is processed in the Preprocessing Module. In this stage, all images are resized to a fixed resolution to ensure consistency during model training. Normalization is performed to scale pixel values and improve convergence during learning. Noise reduction techniques eliminate unwanted distortions caused by weather conditions or image sensors, while data augmentation methods such as rotation, flipping, zooming, and brightness adjustment increase dataset diversity and improve the model's ability to generalize to unseen data. Image enhancement further improves the visibility of structural details such as cracks, roof damage, and collapsed walls.

The preprocessed image pairs are then provided as input to the Feature-Concentrated Siamese Neural Network (FC-SNN), which forms the core of the proposed system. The Siamese architecture contains two identical Convolutional Neural Network (CNN) branches that share the same weights. One branch processes the pre-disaster image while the other processes the post-disaster image. Because both branches use identical parameters, they extract comparable deep features from both images, ensuring consistent representation of structural characteristics.

Following feature extraction, the architecture incorporates a Feature Concentration Module, which functions as an attention mechanism. Instead of treating all extracted features equally, this module emphasizes the most informative structural characteristics while suppressing redundant or irrelevant information. Important damage indicators such as roof collapse, wall cracks, façade deterioration, debris accumulation, and structural deformation receive greater attention, allowing the model to generate highly discriminative feature representations for accurate comparison.

The concentrated feature vectors produced by both branches are then forwarded to the Similarity Comparison Module. Here, a similarity measurement technique, such as Euclidean distance, calculates the difference between the two feature representations. Smaller distances indicate little or no structural change, whereas larger distances indicate significant building damage. This comparative learning approach enables the system to distinguish actual structural damage from environmental variations such as lighting differences, camera angles, shadows, or seasonal changes.

VI. RESULTS AND DISCUSSION

The proposed Building Damage Assessment Using Feature-Concentrated Siamese Neural Network (FC-SNN) was evaluated using paired pre-disaster and post-disaster building images to assess its capability in detecting and classifying structural damage. The dataset included buildings affected by natural disasters such as earthquakes, floods, cyclones, and explosions, with damage categorized into predefined severity levels such as No Damage, Minor Damage, Major Damage, and Destroyed. During preprocessing, images were resized, normalized, and augmented to improve the model's generalization ability. The Siamese Neural Network extracted deep feature representations from both image pairs and used a feature concentration mechanism to focus on the most significant structural changes while minimizing irrelevant variations caused by lighting, shadows, or viewpoint differences.

The experimental results demonstrate that the proposed FC-SNN effectively identifies structural damage by learning feature similarities between pre-disaster and post-disaster images. Compared with conventional Convolutional Neural Network (CNN) models, the proposed approach produced more accurate damage classification with fewer false detections. The feature concentration mechanism significantly improved the model's ability to detect cracks, collapsed roofs, damaged walls, façade deterioration, and partially destroyed structures. The Siamese architecture also enhanced robustness by focusing on meaningful structural changes rather than simple pixel-level differences.

The performance of the proposed model was evaluated using standard classification metrics including Accuracy, Precision, Recall, F1-Score, and Loss. The FC-SNN achieved an overall Accuracy of 98.62%, Precision of 98.15%, Recall of 98.43%, and an F1-Score of 98.29%, outperforming traditional CNN-based approaches. The training and validation accuracy curves showed steady convergence with minimal overfitting, while the loss values consistently decreased throughout the training process, indicating stable learning and good generalization performance.

The confusion matrix further confirmed that the majority of damaged and non-damaged buildings were correctly classified, with only a small number of misclassifications occurring between adjacent damage severity categories. This indicates that the proposed framework can reliably distinguish subtle differences in structural damage, making it suitable for real-world disaster response scenarios.

Overall, the experimental findings demonstrate that the Feature-Concentrated Siamese Neural Network provides a fast, accurate, and scalable solution for automated building damage assessment. Its ability to compare paired images and extract discriminative structural features makes it highly effective for post-disaster analysis. The proposed framework can support emergency responders, government agencies, insurance organizations, and disaster management authorities by providing timely and reliable information for rescue planning, damage estimation, and infrastructure recovery. Future work can further improve the system by incorporating multi-temporal satellite imagery, drone-based aerial images, and transformer-based deep learning models to enhance performance across diverse disaster environments.

VII. CONCLUSION

This research presented an intelligent Building Damage Assessment framework based on a Feature-Concentrated Siamese Neural Network (FC-SNN) for accurately identifying and classifying structural damage using paired pre-disaster and post-disaster images. The proposed approach combines comparative feature learning with a feature concentration mechanism to effectively capture critical structural changes while minimizing the influence of irrelevant background information and environmental variations. By emphasizing significant damage indicators such as roof collapse, wall cracks, façade deterioration, and structural deformation, the model achieves reliable and precise damage classification across multiple severity levels.

The experimental results demonstrate that the proposed FC-SNN outperforms conventional deep learning models by achieving higher accuracy, precision, recall, and F1-score while reducing false positive and false negative predictions. The shared-weight Siamese architecture enables effective comparison of image pairs, making the system robust against changes in illumination, viewing angle, shadows, and weather conditions. Furthermore, the automated assessment process significantly reduces the time and manual effort required for post-disaster building inspection, enabling rapid and scalable damage evaluation for large geographical areas.

Overall, the proposed framework provides an efficient, reliable, and practical solution for automated building damage assessment. It has significant potential for real-world deployment in disaster management systems, satellite and UAV-based monitoring platforms, insurance claim verification, and infrastructure recovery planning. By supporting faster and more accurate damage assessment, the proposed system contributes to improved emergency response, optimized resource allocation, and enhanced urban resilience following natural or human-induced disasters.

VIII. FUTURE SCOPE

The proposed Building Damage Assessment Using Feature-Concentrated Siamese Neural Network (FC-SNN) offers a strong foundation for intelligent post-disaster assessment and can be further enhanced in several ways. Future research can focus on integrating advanced attention mechanisms and transformer-based vision models to improve feature representation and capture complex structural patterns more effectively. Training the model on larger and more diverse datasets collected from multiple disaster scenarios, including earthquakes, floods, hurricanes, wildfires, and explosions, would further improve its robustness and generalization capability across different geographical regions and building types. Additionally, incorporating high-resolution satellite imagery, drone-based aerial images, and multi-sensor remote sensing data can enhance the precision of damage detection in complex environments.

Another promising direction is the development of a real-time damage assessment system that operates on edge devices or cloud-based platforms, enabling rapid analysis immediately after a disaster. Integration with Geographic Information Systems (GIS), Internet of Things (IoT) sensors, and disaster management platforms can provide location-aware damage mapping and support faster emergency response. Future work may also explore 3D building reconstruction, multimodal data fusion using LiDAR and thermal imagery, and explainable artificial intelligence (XAI) techniques to improve the transparency and interpretability of model predictions. These advancements will make the proposed framework more reliable, scalable, and suitable for practical deployment in smart cities, infrastructure monitoring, insurance claim assessment, and large-scale disaster recovery operations, ultimately contributing to safer and more resilient communities.

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