Smart Structures and Systems, *Vol. 31, No. 4 (2023) 311-323*
https://doi.org/10.12989/sss.2023.31.4.311

Computer vision and deep learning-based post-earthquake intelligent assessment of engineering structures: Technological status and challenges

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(*Received October 24, 2022, Revised December 31, 2022, Accepted March 3, 2023*)

Abstract. Ever since ancient times, earthquakes have been a major threat to the civil infrastructures and the safety of human beings. The majority of casualties in earthquake disasters are caused by the damaged civil infrastructures but not by the earthquake itself. Therefore, the efficient and accurate post-earthquake assessment of the conditions of structural damage has been an urgent need for human society. Traditional ways for post-earthquake structural assessment rely heavily on field investigation by experienced experts, yet, it is inevitably subjective and inefficient. Structural response data are also applied to assess the damage; however, it requires mounted sensor networks in advance and it is not intuitional. As many types of damaged states of structures are visible, computer vision-based post-earthquake structural assessment has attracted great attention among the engineers and scholars. With the development of image acquisition sensors, computing resources and deep learning algorithms, deep learning-based post-earthquake structural assessment has gradually shown potential in dealing with image acquisition and processing tasks. This paper comprehensively reviews the state-of-the-art studies of deep learning-based post-earthquake structural assessment in recent years. The conventional way of image processing and machine learning-based structural assessment are presented briefly. The workflow of the methodology for computer vision and deep learning-based post-earthquake structural assessment was introduced. Then, applications of assessment for multiple civil infrastructures are presented in detail. Finally, the challenges of current studies are summarized for reference in future works to improve the efficiency, robustness and accuracy in this field.

Keywords: computer vision; deep learning; post-earthquake structural assessment; satellite; unmanned aerial vehicle

1. Introduction

The earthquake is one of the most devastating natural disasters that can seriously damage civil infrastructures (Holden *et al*. 2003, Bonnefoy-Claudet *et al*. 2006, Hu *et al*. 2022). The vertical and horizontal ground motion induced by earthquakes can damage the columns of the buildings or the piers of the bridges and break the connection that might lead to partial damage or even to collapse (Hashash *et al*. 2001, Boore and Atkinson 2008). Additionally, the area of influence of earthquakes can cover a whole city or even many cities (Sezen *et al*. 2003, Rao and Satyam 2022). Therefore, it is of great importance to acquire the damaged levels of influenced infrastructures for post-earthquake rescue (Lagomarsino and Giovinazzi 2006, Jalayer and Cornell 2009). Conventional methods for the assessment of the conditions of the damage incurred by infrastructures rely heavily on on-site manual inspection that is labour-intensive, expensive, insecure, etc., (Binda *et al*. 2000, Chang *et al*. 2022). What's more, the delayed manual inspection process might slow down the speed for the evacuation or rescue operations that are critical for the citizens in earthquake regions (Shang *et al*. 2022, Zhang *et al*. 2022a).

The post-earthquake assessment of structural damage is based on the structural response data, which is mainly two types: sequence data and image data. Scholars in the field of civil engineering are very familiar with sequence data such as ground and structure deformation (Xu *et al*. 2005, Kaloop and Kim 2014). Kim *et al*. (2020) proposed a framework using deep-learning methods to make critical advances in pre- and post-earthquake regional loss assessments. The framework also used a new adaptive algorithm to find the optimal locations and number of additional sensors in the urban community for post-earthquake decision-making. Xu *et al*. (2021) proposed a framework for real-time assessment of regional seismic damage based on a Long Short-Term Memory (LSTM) neural network architecture. Kim and Song (2022) proposed a DNN-based framework to identify seismic damage based on structural response of earthquake data and verified by a 5-story, 5-bay steel frame structure. Li *et al*. (2021). proposed a method that combined the interstory drift spectrum and a deep-learning method to estimate the maximum interstory drift ratio (MIDR) to estimate the buildings' MIDR of seismic events. Huang *et al*. (2021) presented a deep learning-based technique to automatically estimate the local slope map from the seismic data. Fayaz and Galasso (2022) presented a Real-time on-site estimation of response spectra (ROSERS) to estimate the acceleration

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http://www.techno-press.org/?journal=sss&subpage=7
ISSN: 1738-1584 (Print), 1738-1991 (Online)

response spectrum of the expected on-site ground-motion waveforms. Yu *et al*. (2019) proposed a novel method based on deep convolutional neural networks (CNNs) to identify and localize damage to building structures. However, it is difficult to install large numbers of sensors throughout a vast land area, which makes this sequence data-based method uneconomical in terms of a city scale.

Since plenty of damage such as cracks, spalling, or even collapse is visible, vision-based investigations were conducted previously by the inspectors as an important method for initial and quick inspection (Spencer *et al*. 2019). Nonetheless, the assessment based on the estimation of human inspectors is vague and subjective. With the development of image sensors and image processing algorithms, the computer vision-based assessment of the detection of post-earthquake damage and assessment of the conditions of civil infrastructures is gradually being adopted by engineers and scholars in the sector (Bao *et al*. 2019, Ye *et al*. 2021). The large-scale and remote sensing capacity of image sensors satisfies the demand for post-earthquake inspection on a large scale well (Ye *et al*. 2022). The first attempt at vision-based post-earthquake damage condition assessment dates back to the year of 1906, when G.R. Laurence acquired the images of San Francisco by a kite-mounted camera (Duffy and Anderson 2016). Since then, all kinds of computer vision-based applications for the assessment of post-earthquake damage conditions have been developed world wide (Matin and Pradhan 2021).

Based on the difference regarding image acquisition, these methods can be roughly divided into satellite-based damage assessment, unmanned aerial vehicle (UAV)-based damage assessment and ground photographing-based damage assessment (Massonnet *et al*. 1993, Guzzetti *et al*. 2012, Zhao *et al*. 2022). The satellite-based damage assessment is conducted by acquiring the images of the ground situation through multiple kinds of satellite-mounted image sensing devices, such as optical cameras, infrared cameras, synthetic aperture radar (SAR), etc., (Dai *et al*. 2022, Luo *et al*. 2022). This method could obtain the ground image on a large scale, which is suitable for district level assessment. Besides, The SAR system could penetrate the clouds that might be blocking the optical image acquiring device (Xiong *et al*. 2022). Yet, the timeliness of satellite-based damage assessment is not quite satisfactory enough, since the operation can be conducted only when the satellites pass nearby. The UAV-based damage assessment is an emerging approach to meet the demand for fast assessment of infrastructures damaged by earthquakes, where ground traffic is probably destroyed (Rosen *et al*. 2007, Nedjati *et al*. 2016, Dominici *et al*. 2017). Nowadays, the UAVs are smarter with longer ranges that are suitable for reaching hotspots (Baiocchi *et al*. 2014, Kakooei and Baleghi 2017). Also, high resolution cameras allow detailed capturing of buildings or bridges that facilitate quantified estimation of damage levels (Freeman *et al*. 2019). The timeliness is better than the satellite-based damage assessment and it is more of a structure-level detection approach that is suitable for the damage detection of a whole structure or part of the structure (Li *et al*. 2011). Yet, the weather conditions, especially wind or rain, will greatly influence this approach, since the stability of the flight is of critical importance. As for the ground photographing-based damage assessment, it is much the same as the way it is done for image-based detection of routine inspection of infrastructures (Bemis *et al*. 2014, Ye *et al*. 2019). Cameras or portable devices are adopted for image acquisition of damaged structures. It is a step closer to the structures and more details can be recorded such as cracks, spalling, etc. It might help to quantify the damaged areas of a structural component and provide reference for other assessment methods such as numerical estimation or on-site testing.

Aside from the way the images of the damaged structures are obtained, it is also important to process the images of damaged structures to extract the structural states, damage levels or even quantify the detailed damages. After the period of determination by trained experts, image processing techniques were used for damage assessment (Gorgin and Wang 2021, Wang *et al*. 2021a, b). However, these methods are more of a threshold-based approach by detecting hand-made indices. On the one hand, these indices are often proposed by trained experts that can easily be subjective and biased. On the other hand, the images often contain many noise motifs that can mislead these approaches, such as the shadows and reflections of buildings in satellite-captured images (Chini *et al*. 2008). In addition, the machine learning-based approaches have been investigated including artificial neural networks (ANNs), support vector machines (SVMs), Bayesian inference, etc., (Kubat *et al*. 1998, Dramsch 2020). These methods can learn and establish the relationships between the extracted features and damaged states (Riedel *et al*. 2015). Yet, the features are usually determined by the experts and extracted with detailed methods, that is not automatic and smart enough. Nowadays, the development of deep learning-based approaches provides a novel alternative to dealing with the damage identification process in post-earthquake scenarios (Seydi *et al*. 2022, Kamari *et al*. 2022). By learning from the raw image data itself, the DNNs can establish directly between the input image and the damage condition, with much less interference of human experts (LeCun *et al*. 2015). Engineers and scholars focusing on this domain have taken efforts to gradually bring in this new technique to improve the accuracy of post-earthquake damage assessment.

This paper reviews the state-of-the-art studies on computer vision and deep learning-based post-earthquake assessment of civil infrastructures. The organization of the paper is as follows: Section 2 introduces the methodology of computer vision-based structural damage assessment. Section 3 presents the applications of computer vision and deep learning-based post-earthquake assessment of civil infrastructures. Section 4 points out the main challenges and future development of deep learning in post-earthquake structural assessment. Section 5 addresses the conclusions from the discussion in the paper.

2. Methodology of computer vision-based structural damage assessment

The application of computer vision-based structural damage assessment can be roughly divided into three parts:

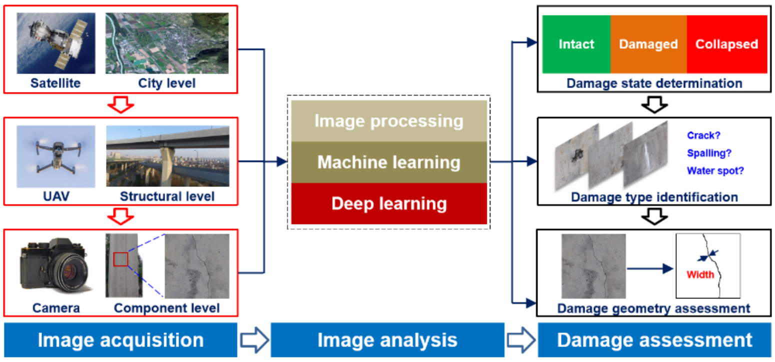

Fig. 1 Flowchart of computer vision-based structural damage assessment

image acquisition, image analysis and damage assessment. After the acquisition of structural images, the image analysis is conducted. Based on the difference in principle, the methodology for image analysis methods can be divided into image processing techniques, machine learning and deep learning. Then, based on the image analysis, the damage assessment is estimated. From coarse to fine, the structural state of whether or not a structure is damaged and how intensely it is damaged are determined. Then, the component behavior is assessed for whether they are damaged and what the damage types are. Finally, detailed damage states such as crack width, length or spalling area will be obtained. A brief introduction to the methodology of computer vision-based structural damage assessment for post-earthquake scenarios is shown in Fig. 1.

2.1 Image acquisition approach

Since the post-earthquake scenarios are special because the transportation system might be destroyed, the image acquisition is slightly different. The satellite-based image acquisition offers stable approach when ground traffic is not convenient to use (Tronin 2009, Saba *et al*. 2022, Zhang *et al*. 2022b). There are usually two types of satellites: low orbit satellites and synchronous satellites. The low orbit satellites stay in an orbit that is 200 to 5,000 kilometers above the ground. Multiple types of imaging acquisition systems can be used for ground image capturing at this altitude and they have a relatively high image resolution. However, stability and continuity are poor, since the satellites will fly over the target area quickly. The synchronous satellites stay in the geosynchronous orbit that is 36,000 kilometers above the ground, and have the same speed of rotation as that of the earth. The onboard image system can acquire along a large range of area and take stable and fast shots, but the resolution is low.

These satellites can obtain three kinds of images according to different sensors: infrared images, radar images and visible (optical) images (Ouzounov *et al*. 2006, Yao and Qiang 2012). The image formed by an infrared remote sensor carries a specific line band invisible to the human eye, which has the characteristics of strong penetration but low resolution and poor imaging quality (Fu and Lin 2003). The radar images are those formed by the echo signal received by the radar antenna, after scanning the

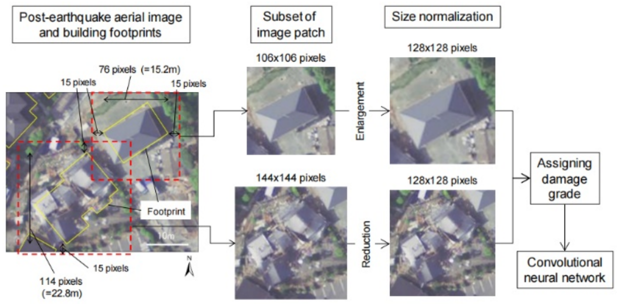

Fig. 2 Resolution of aerial images (Miura et al. 2020)

object by transmitting a microwave beam, which is affected by the size of the antenna (Matsuoka and Nojima 2010). Notably, the synthetic aperture radar (SAR) is one type of radar with high resolution, strong penetration, low sensitivity to meteorological conditions with all-weather work capacity (Balz and Liao 2010, Wang *et al*. 2015). The visible (optical) images are those formed by the electromagnetic wave band that can be perceived by human eyes. It has the characteristics of clear image texture, high resolution and wide adaptability (Huang *et al*. 2017). But it is easily affected by the external environment, such as bad weather (Dong *et al*. 2011).

Besides, the industrial UAV-based method can capture the images of damaged structures dozens of kilometers away (Cao *et al*. 2016). They can integrate camera, professional radar, infrared remote sensing and other imaging equipment, and obtain pictures with certain penetration, high resolution, or in a non-visible band (Sun *et al*. 2022). Nowadays, consumer grade UAVs are also equipped with cameras with a range of several kilometers (Verykokou *et al*. 2018). Images are captured by onboard cameras, ordinary cameras, mobile phones and other small devices, which are convenient and widely applicable. Nonetheless, consumer grade UAVs are susceptible to environmental conditions and are unable to perform prolonged or special operations. Since aerial images are taken from quite a distance away, the resolution image is typically larger than 0.5 m/pixel, as shown in Fig. 2. (Amirkolaee and Arefi 2019, Miura *et al*. 2020). Additionally, when the earthquake is not severe, portable devices such as cameras or mobile phones can be used by inspectors directly.

2.2 Image analysis and damage assessment

Image analysis is the key step to extract structural damage information for automatic damage assessment. Before the booming of deep learning-based image analysis, image processing and machine learning techniques had also been investigated by researchers worldwide.

In terms of image processing techniques, the features of the target damage were often utilized for damage detection. As for local damage detection, the geometry features were often used. Regarding the crack detection, Zhu *et al*. (2011) presented a novel method of retrieving crack properties. The method located crack points through crack detection techniques to identify the skeleton configurations of the points and calculated the distance field of crack points through a distance transformation. The approach could automatically retrieve crack width, length, and orientation. Ebrahimkhanlou *et al*. (2015) proposed a novel method to circumvent the erroneous Visual Inspection (VI) of reinforced concrete shear walls (RCSW) by utilizing the information hidden in crack patterns. The method automatically extracted crack patterns from images of the surface cracks on RCSWs, and applied Multifractal Analysis (MFA) on the crack. The result showed that MFA had correlation with the tri-linear shear-controlled behavior of walls in backbone curves. Regarding the detection of spalling, German *et al*. (2012) proposed a method for identifying the spalling of reinforced concrete columns. A threshold algorithm based on local entropy of the spalling area was used to segment the tribal area, and the degree of spalling was divided into three categories to identify and quantify the length of the spalling. The highest rate of accuracy was 81.1%, and the recall rate was 81.1%. up to 80.2%.

As for the detection of building damage, such as structural collapse, the geometry features can also be utilized for detection. Wang *et al*. (2020) proposed an approach for extracting intact and collapsed buildings via multi-scale morphological profiles with multi-structuring elements. The method established linear and disk structuring elements to extract the initial buildings and used straightforward threshold segmentation and further post processing to obtain buildings. Via experiments, the method could identify the earthquake-damaged building. Besides, the color features of the buildings were also investigated for classification of structural collapse. Xu *et al*. (2012) presented a building detection approach based on HSV color space and proposed a building damage detection algorithm. The method was based on the gray level histogram features which can separate the housing construction units, and the identification results obtained were consistent with the results of artificial visual interpretation. Moreover, the Wishart distribution of the building features can be used as well. Zhai *et al*. (2018) focused on rapid detection of earthquake damage to buildings in urban areas using a single post-earthquake polarimetric synthetic aperture radar (PolSAR) image. The author proposed the two new polarimetric feature parameters to recognize buildings and employed the Wishart supervised classification method to improve the accuracy of the extraction of the damaged buildings. The method was simple and easy to operate and was suitable for rapid post-earthquake emergency response.

Except for the detection of damage, quantified estimation of the damage can be obtained with high resolution images. Liou *et al*. (2010) utilized the high-resolution satellite-based images of before and after the earthquakes to analyze the potential disasters, and conducted quantified estimation of the damaged areas. Liu *et al*. (2016) presented a polarimetric radar system to sense the concealed wood-frames damaged by earthquakes. The system employs four linearly polarized antennas to record radar echoes. Through experiments, the method showed that a polarimetric radar system could provide much richer information on the condition of concealed building structures than the conventional single-polarization radar. Brunner *et al*. (2011) analyzed the SAR data of TerraSAR-X meter resolution and Memphis decimeter resolution after the earthquake. The experimental results showed that the meter resolution data could only judge whether the building was damaged, but could not determine the degree of that damage, while the decimeter resolution could be used to classify the degree of the damage.

Nonetheless, the image processing-based damage detection approaches usually made use of a predefined set of features to detect target damage with the threshold-based methods. They are effective in specialized cases with repeated threshold modification. When dealing with images of earthquake-affected areas, it is difficult to transfer one method to another scenario with different backgrounds and image resolutions.

Compared with the image processing-based techniques, the machine learning-based techniques were improved a step further to identify post-earthquake structural damage. The main process of machine learning-based post-earthquake damage detection methods contains two steps: feature extraction and classification. The features of damaged buildings, the intact buildings and the background were obtained with multiple extractors simultaneously. Then, the classifier was used to classify or detect the damaged structures.

The multi-level features of structural elements will be affected by the earthquake and thus can be used for damage detection. Carreno *et al*. (2010) proposed a computational tool to assist the damage and safety evaluation of buildings after strong earthquakes. A four-level ANN was used to classify the damage status of structures, based on the status of multiple structural elements. Two applications of the computational tool showed the feasibility for the evaluation of damage to building. The features of the edges of the roofs of buildings were also investigated for damage detection. Dong *et al*. (2014) obtained the edge-fitting straight line information by means of the Douglas-Paeucker algorithm, and input the straight line information and weighted inclination standard deviation information of the damaged building satellite image into the linear SVM to judge whether the building was damaged or not, and carried out the damage assessment of skylight time. The spectral characteristics of the ground images before and after the earthquake offered other options for damage detection.

Syifa *et al*. (2019) used the ANN and SVM classifier to jointly classify the damage of two types of damage cloud images of Landsat-8 and Sentinel-2 after the earthquake, based on three multispectral bands of the images. Afterwards, the post-earthquake damage map was generated. Compared with the field data, the cloud map generated by Landsat-8 had a higher coincidence rate, and the post-earthquake damage map could be used to evaluate the damage of the Palu earthquake.

In terms of accuracy of detection, since the shooting distance of the images is not identical for different buildings, preprocessing can be useful in guaranteeing the accuracy of detection. Khodaverdi zahraee and Rastiveis (2017) used the satellite images before and after the earthquake to automatically draw a map of the damaged buildings after the earthquake. The images were first preprocessed to unify the building sizes. Then, seven features related to the changes of buildings were extracted and the ANN was trained to classify the changed and unchanged areas. The overall accuracy of the method was 93% after verification. Denoising is found to effectively improve the accuracy of detection. Wang and Li (2015) used the post-earthquake VHR image combined with lidar to extract the region of the undamaged building in the map. Then, the pre-earthquake VHR image was utilized to eliminate the undamaged building area for accurate detection of the damaged building regions. The One-Class Support Vector Machine (OCSVM) was used to conduct the classification of structural damage. The experimental results showed that the proposed method increased the Kappa coefficient of damaged buildings by 21%.

Compared with image processing-based methods, two main improvements were achieved in the main steps of the machine learning-based methods. First of all, as can be seen from the machine-learning based studies, more intuitional and latent features of the images can be used for detection of structural damage. Consequently, it was possible to deal with more complicated scenarios while the image processing-based methods take merely one or a few features for detection. Second, the classifiers in the machine learning-based methods are able to learn from mistakes regarding how to appropriately classify the damaged from the intact structures. Meanwhile, the image processing-based methods can only define inflexible thresholds for classification.

However, the extractors in machine learning-based methods are usually predefined by the researchers according to the images of the earthquake-stricken areas. Thus, they are subjectively determined. Moreover, unknown latent features of the structures might exist. Thus, their capacity for generalization is limited. With the development of hardware and related algorithms, the deep learning emerged with the ability to establish the relationship between the result and the input autonomously. Thus, it has drawn great attention and was applied to damage detection of post-earthquake scenarios worldwide (Alipour *et al*. 2019, Azimi *et al*. 2020, Mantawy and Mantawy 2022). A detailed discussion of deep learning-based studies is can be found in section 3.

3. Applications of computer vision and deep learning-based post-earthquake structural assessment

Similar to all kinds of deep learning-based applications in other sectors, the main composition in the framework of the applications of computer vision and deep learning-based post-earthquake structural assessment contain three parts: the dataset, the model training, and the assessment results. Meanwhile, there exist unique issues to be solved for successful post-earthquake structural assessment.

3.1 Structural assessment with imbalanced datasets

The satellite stays in its orbit and captures the ground images via onboard cameras. Due to the limit of image resolutions, preliminary judgement of the structural state is usually made into three categories: damaged, partly damaged and intact. However, in earthquake-affected areas, the majority of the structures are usually intact, while some of the damaged buildings do not have obvious deformation on the tops such as the roof structures. Thus, there is a problem of imbalanced image samples that will mislead the training DNNs. To solve the lack of damaged samples, Miyamoto and Yamamoto (2021) outlined an earthquake damage detection system based on 3-D CNN and satellite photographic images to understand regional residential earthquake damage. Images of pre- and post-earthquakes were adopted to detect damage to single buildings. The method achieved over 90% detection accuracy on damaged housing in the affected area of the 2016 Kumamoto earthquake, in Japan. As is shown in Fig. 3, the utilization of pre- and post-earthquake images offered contrastive features for the DNNs to identify structural damage. Meanwhile, the adding of structural information provided

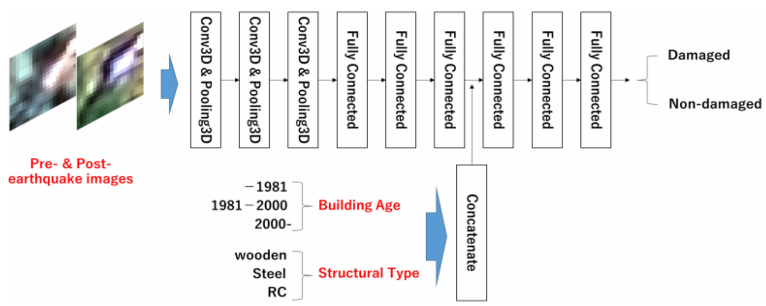

Fig. 3 CNN-based damage assessment (Miyamoto and Yamamoto 2021)

information of other dimensions to improve the accuracy of detection. Ji *et al*. (2018) used three balancing methods: cost-sensitive, random over-sampling and random under-sampling. The balanced SqueezeNet is effective in judging whether it was a collapsed building, and the Kappa value reached 41.6%. The PA was better in identifying the degree of damage, and the highest Kappa value was 61.1%. Amirkolaee and Arefi (2019) proposed a novel approach to identifying collapsed buildings after an earthquake that could estimate DHM using only single satellite images. In their study, a strategy for structural reconstruction was designed to improve estimated height values and the geometry of objects. The quality, kappa coefficient and overall accuracy of the results obtained were 84.86%, 91.15% and 98.78%, and demonstrated a promising performance of the proposed approach.

Similar to an imbalanced dataset problem in the satellite-based post-earthquake structural assessment, the UAV-based ones were also challenged. A direct way was to literally renew the obtained damage data, as was done by Miura *et al*. (2020). They proposed a methodology for the automated identification of building damage based on CNN and building damage inventories. Noteworthy was the fact that the framework used remote sensing-based damage detection and constantly updated the collected new damage information. Alternative measures could be assistance from machine learning approaches. For instance, Sajedi and Liang (2019) proposed a semantic segmentation framework to recognize surface cracks. The imbalanced problem of data categories was overcome by the adoption of Bayesian optimization. The robustness of the framework was verified by extracting crack shapes from real unprocessed images captured by UAVs. Evaluation of accuracy and recall reflected the wide application of UAVs in further visual inspection.

3.2 Quantification of structural damage

The quantification of structural damage contains the acquirement of geometry and location of the detected structural damage. The geometry of the damage is quite important for the determination of the safety of target structures. Inserting markers in the images might provide reference for the calculation of nearby damage. Kim *et al*. (2018) investigated a method for deep learning-based crack identification by the combination of a commercial UAV and a high resolution vision sensor. The geometry of the crack was obtained by adding a reference marker on the inspected bridge. A field test was conducted to verify the proposed approach, and the results indicated that the UAV-based bridge inspection was effective in identifying and quantifying the cracks on aged bridges. For quantized assessment, an image process technique was also helpful. Huynh *et al*. (2019) used the feature that UAV could shoot relatively clear and robust connection images to estimate the angle of rotation of bolts from connection images. The deep learning was combined with image processing to estimate the accurate angle of loosened bolts. What's more, 3D images of the same damage could be used for estimation of 3D geometry. For an accurate description of the level of the damage, Dizaji and Harris (2019) proposed a novel framework based on deep 3D CNN, which learned the features of 3D defects from a 3D dataset intended to mimic defects on the surface of concrete columns. As shown in Fig. 4, The 2D dataset was used to detect the structural spalling on the beam and the 3D dataset was for the estimation of the volume of the spalling. The large simulated 3D defect dataset including 12000 samples was automatically constructed with labeled defect features for training the model. The learned 3D CNN yielded a training and validation accuracy of 98.85% and 96.46% which showed the feasibility and potentials of this approach for 3D detection of defects.

The location of the structural damage is another major concern for post-earthquake assessment. The use of the bounding box in target detection models can provide a planimetric position on the sensing images. Ma *et al*. (2019) applied the YOLOv3 to locate collapsed buildings from post-earthquake remote sensing images. The method replaced the Darknet53 CNN in YOLOv3 with the lightweight CNN ShuffleNet v2 and used the generalized intersection over union (GIoU) loss. The speed of detection was improved by 5.21 f/s and precision was improved by 5.24%, and the improved model had stronger noise immunity capabilities. As a consequence, the selection of optimal DNN models was explored for better detection. Fu *et al*. (2022) used post-earthquake UVA images to train the Mask R-CNN network to identify earthquake landslides,

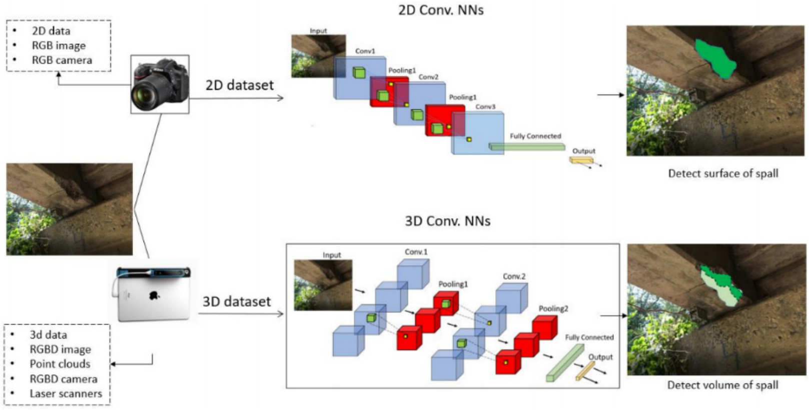

Fig. 4 3D camera-based damage detection (Dizaji and Harris 2019)

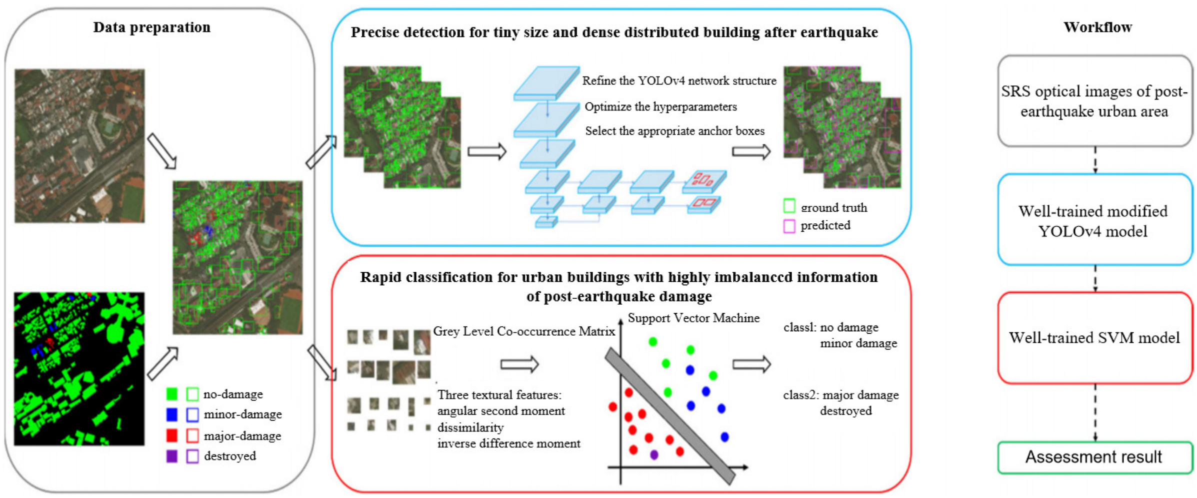

Fig. 5 CNN and SVM based damage assessment (Wang *et al*. 2022)

with ResNet-50, ResNet-101 and Swin Transformer as backbone networks, respectively. Data augmentation and transfer learning were utilized to release the requirement for image samples. The results showed that due to the other two networks, the accuracy and F1 values of Swin Transformer network were 0.9328 and 0.9025 respectively.

Another effective way is to locate the position of the sensing equipment. Since, the GPS is not always available, local navigations were used. The UAVs can locate themselves by GPS and fly along a planned routine around the target structure to capture the surface images (Achille *et al*. 2015). Kang and Cha (2018) proposed a UAV-based method with ultrasonic beacons to replace the role of GPS, and a deep CNN was used for damage detection, while a geo-tagging method was used for the localization of damage. Three different UAV autonomous indoor tests were used to process the video data collected by the UAV, and the concrete cracks were detected successfully. Besides, another case was found that made use of vision-based approaches. Narazaki *et al*. (2022) proposed an approach for vision-based autonomous navigation planning of UAVs for the collection of images, which was suitable for the rapid post-earthquake inspection of reinforced concrete railway viaducts. Tests on a railway viaduct indicated the columns were detected completely and robustly with centimeter-level accuracy.

3.3 Classification of structural damage levels

As the post-earthquake relief operation relies on the status of the damaged structures, the classification of structural damage is a major concern for engineers and decision-makers. The DNNs can conduct classification of multiple categories, thus, direct classification was possible solely with the DNN model. Xu *et al*. (2019) used the improved Faster R-CNN network to accurately classify multiple bits of damage to concrete columns after an earthquake. Besides, by adjusting the super parameters of the model, the average accuracy reached 80%, and the highest accuracy reached 94.4%. However, as the remote sensing cannot always capture obvious features for clear classification, post-processing algorithms were adopted for the determination of levels of damage. Song *et al*. (2020) utilized DeepLabv2 to preliminarily divide the area of damaged structures during the earthquake, and used the SLIC method to segment the edges of damaged structures. After the fusion of images from the above two steps, the combined images were denoised to obtain the rapid extraction of damaged structures after earthquakes. In addition, machine learning could be used to focus on the classification of detected damage. Wang *et al*. (2022) proposed a two-stage damage assessment method for post-earthquake buildings. As shown in Fig. 5, the fused multi-scale features of buildings in satellite remote sensing SRS images were extracted by the optimized YOLOv4 model for damage detection. These damage features were located through the SRS optical images of the gray co-occurrence matrix. Then the SVM model was used to identify the texture features of buildings after the earthquake to determine the degree of damage. The accuracy of the average location of this method was more than 95.7%, and the binary assessment of earthquake damage was more than 97.1%. Besides, for refined determination of the level of damage, the assessment of the damage to structural components was carried out. Zou *et al*. (2022) proposed a method for assessing the component failure mode and level of damage. Based on the type and extent of damage, damage levels were quantitatively evaluated. A YOLOv4 network was used to detect multi-category damages. Regarding depth, separable convolution was introduced, which increased the speed of detection by 10% and reduced computation costs by 42% without reducing accuracy. A GUI was developed to combine the method of assessing damage and the method of detecting damage. The assessment results indicated that the GUI was accurate and could assist inspectors by increasing the efficiency and safety of post-earthquake investigations.

3.4 Generalization of the trained models

Earthquakes can happen in areas with different structural conditions and ground situations, thus, to improve the generalization of the trained models it is essential to reduce repeated investment. The utilization of multi-source image data and detection denoising are effective methods. Nex *et al*. (2019) tested an advanced CNN for visual detection of structural damage and found that the composition of training samples had an impact on quality metrics. Post-earthquake images from space, aerial and UAV platforms were used and transfer learning was applied to test the transferability. Rajput *et al*. (2020) collected the data of six different types of natural disasters in xView2, and quantified the degree of the damage to buildings before and after the earthquake. They established the comprehensive framework of earthquake management combined with Internet of things, sensor network and deep learning model. Duarte *et al*. (2020) tested six multi-temporal and three mono-temporal approaches to analyze pre-event and post-event images of facade damage. They also assessed the image classification with multi-temporal aerial oblique imagery. Ghorbanzadeh *et al*. (2019) used the optical data collected by UVA to input CNNs of different depth to generate eight different slope failure distribution maps. Compared with the manually labeled distribution maps, the best CNN network combined the slope data with an accuracy of 90%, and the F score reached 85%. Additionally, field investigation data of slope deformation was used for reference. The results indicated the multi-temporal approaches had a higher accuracy of identifying damage to buildings. Jing *et al*. (2022) proposed the YOLOv5s-ViT-BiFPN network, which combined the vision transformer structure to enhance the structural characteristics of damaged houses. The BiFPN structure was introduced to cluster different resolution features. The experimental results showed that the average accuracy of this method was 9.31% and was 1.23% higher than that of YOLOv3 and YOLOv5. Meanwhile, the speed of detection was 2.96 times faster than that of YOLOv3. Except for multi-source damage data, complicated sensing conditions were also investigated. Santos *et al*. (2022) proposed a technique for automated detection of exposed steel rebars, which was integrated into the video system of a drone with GPS geo-parameters. The tools were developed on AlexNet and transfer-learning was used for compensation of data shortage. The results of field experiments showed that the proposed methods had better stability in complex external environments such as variable lightning exposure, and the results obtained also had high adaptability to structure detection, shown in Fig. 6.

Except for the studies focusing on the detection of earthquake-induced damage, the deep learning-based studies aiming at daily inspection can also provide reference for deep learning-based assessment of damage (Tang *et al*. 2019, Sony *et al*. 2021).

4. Challenges of deep learning in post-earthquake structural assessment

Deep learning-based applications have been carried out among engineers and scholars in the field of post-earthquake structural assessment. However, there remain multiple challenges that stand in the way for the practical application of deep learning. Based on the review of this paper, the challenging factors are summarized as follows.

(1) The imbalanced problem of structural statues in the image data sample: The detection of damaged structures is based on the deformation of affected engineering structures. When the intensity of the earthquake is not great or if the affected structures are high-strength ones, the damaged sample images often belong to minor ones. As a consequence, the DNNs trained by imbalanced image samples will tend to perceive a testing structure as intact ones. Thus, more images containing damaged structural features should be established by generative models, image augmentation methods, etc., to provide more learning samples. In addition, feature information might be demanded such as the structural ages and structural forms to supplement the supporting information for the DNNs to make better judgement;

(2) The acquisition of the quantification parameters of the damaged structures: As for obtaining the location of the damaged structures, image coordinates, position of the sensing equipment can provide critical information. However, more attempts are still required to efficiently and accurately locate the detected damaged buildings. When it comes to the geometry of the damaged structures, the detected buildings in the captured images usually have all kinds of angles in terms of the image coordinate systems. For instance, the roof of buildings are polygons in the images and the results of the detection expressed by bounding boxes are often larger than the actual buildings. Meanwhile, the

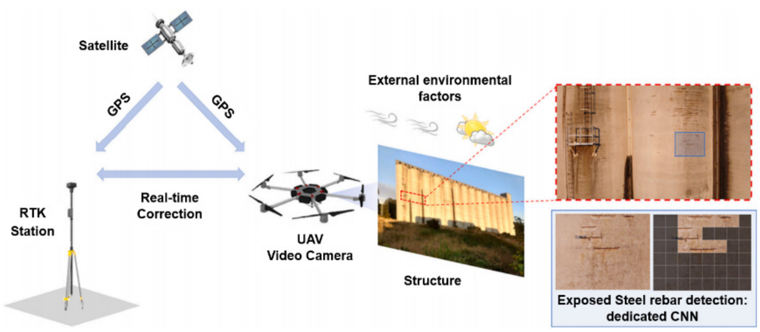

Fig. 6 UAV-based damage assessment (Santos *et al*. 2022)

semantic segmentation approaches could not accurately depict the roof structures, which are often accompanied by incorrect noise detection. As a result, later processing to support disaster relief operations will be less accurate. Thus, morphology-based or machine learning-based methods are still desired to modify the result initially provided by the DNNs;

(3) The accurate determination of levels of structural damage in post-earthquake scenarios: The critical step for deep learning-based post-earthquake structural assessment is to classify the structural damage accurately. Although there exist many successful studies that can detect damage with a high degree of accuracy, the complicated background of the images challenges the application of deep learning-based methods. Thus, model modification or denoising methods are needed to improve the accuracy of detection. In addition, since the damage level varies among different structures, the refined assessments for the degree of damage to different structures or even the damage levels of structural components are still insufficient;

(4) The generalization of trained DNNs in different scenarios: In terms of the remote sensing images of earthquake-affected areas, multiple kinds of images captured by different platforms might exist. On the one hand, these remote sensing methods, including the SAR images, optical satellite images or UAV images, aerial images, helicopter images, etc., have different resolutions and spectral bands. On the other hand, the target structures on a certain area might have different structural features including different structural forms, roof materials, building densities, background, etc. Therefore, it is vital to transfer a trained DNN model or established framework in order to be effective in other image data to make full use of the recorded image data, and implement fast and efficient damage detection for potential target areas. Methods to improve the generalization of deep learning-based approaches for the detection of post-earthquake damage, such as multi-source damage data-based training, transfer learning, etc., still require more investigation; and

(5) The combination of image acquisition and damage detection: The majority of the applications separate image acquisition and image processing steps. Although the deep learning-based approaches offer competitive damage assessment capacity, the fusion of the two steps is desired. Deep learning embedded satellites and UAVs can provide flexible on-site utilization and prompt data processing. A similar application can be seen in security domain, yet, it is rarely seen in post-earthquake relief operations, which are short of studies nowadays.

5. Conclusions

This paper systematically presents the state-of-the-art studies of computer vision and deep learning-based post-earthquake structural assessment. Based on the summary of these studies, the following conclusions can be made:

(1) Satellite-based image acquisition can provide a wide range of the target area but the resolution is not satisfactory enough, which is suitable for the preliminary determination of the structural status; The UAV-based approaches could bring optical cameras and radars according to different requirements, but weather conditions might pose unfavorable challenges;

(2) Image processing methods for structural damage assessment require case-by-case designed feature extraction methods. Meanwhile, the machine learning-based post-earthquake structural assessment methods can make use of more structural features and learn to classify the damage. Yet, the feature extractors are still subjectively predefined. Thus, these two methods are not generalized and are easily influenced in different scenarios;

(3) Deep learning-based post-earthquake structural assessment methods provide great potential for accurate detection and evaluation of damaged structures. Many kinds of studies already exist that made use of deep learning-based methods to detect the damaged buildings after earthquakes. Yet, there are still several challenges, including the imbalanced datasets of damaged structures, the accurate detection and classification of structural damage, the precise obtainment of damage location and geometry, and the generalization of deep learning-based approaches in different scenarios. In addition, although many kinds of DNNs exist, they have not been well embedded into mobile platforms to facilitate fast on-site structural assessment.

Altogether, the deep learning-based post-earthquake structural assessment is now being improved rapidly, even though there are still numerous challenging issues. With the development of carrying platforms, high resolution cameras, DNN models and training strategies, practical applications of computer vision and deep learning-based structural assessment is on the way in disaster relief and decision-making.

Acknowledgments

The work described in this paper was jointly supported by the National Natural Science Foundation of China (Grant No. 52178306), and the China Postdoctoral Science Foundation (Grant No. 2022M712787).

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