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Review

Artificial intelligence-assisted visual inspection for cultural heritage: State-of-the-art review

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ABSTRACT

Applying computer science techniques such as artificial intelligence (AI), deep learning (DL), and computer vision (CV) on digital image data can help monitor and preserve cultural heritage (CH) sites. Defects such as weathering, removal of mortar, joint damage, discoloration, erosion, surface cracks, vegetation, seepage, and vandalism and their propagation with time adversely affect the structural health of CH sites. Several studies have reported damage detection in concrete and bridge structures using AI techniques. However, few studies have quantified defects in CH structures using the AI paradigm, and limited case studies exist for their applications. Hence, the application of AI-assisted visual inspections for CH sites needs to be explored. AI-assisted digital inspections assist inspection professionals and increase confidence levels in the damage assessment of CH buildings. This review summarizes the damage assessment techniques using image processing techniques, focusing mainly on DL techniques applied for CH conservation. Several case study applications of CH buildings are presented where AI can assist in traditional visual inspections.

1. Introduction

Aging of historic constructions, such as cultural heritage (CH) structures, is a major challenge in countries worldwide. Structural health monitoring (SHM) of CH structures with regard to their surface degradation is challenging owing to its slow pace and a lack of comparison between different damage progressions. A key issue is that material deterioration that often starts on the surface, if it progresses sufficiently inside, will eventually lead to damage to building components and affect structural performance. Manual non-automatic visual inspection is one of the traditional techniques and the best starting point for inspecting buildings and surface damage and deterioration. Complex testing procedures should not be initiated without performing this basic step. Traditional visual inspections rely on the person doing the examination and carrying out the recognition, ideally with good efficiency and reliability. However, basic inspection methods, such as non-automatic visual inspections, tend to be expensive and time-consuming, often with unknown uncertainty quality, and in many instances, limited by the sensitivity of human senses for damage identification. Furthermore, there is a problem of repeatability in identifying damaged patches, as each operator is trained differently and has different experiences in identifying damages. This problem becomes prominent when changing inspection operators, making CH monitoring unreliable over longer periods. The inspection operation, depending on the subjectivity of domain experts in identifying damages, may have slight differences in the definition, extension, and severity of the assessed damage [1]. Fig. 1a–c shows various scenarios, such as difficult-to-reach locations in bridge structures where conducting traditional visual inspections is challenging. In these cases, drone-based inspections are a good alternative as they can capture high-resolution images, which can be later analyzed. These will allow damage detection remotely from images and videos from hard-to-reach locations that are dangerous to access from a safety viewpoint. Moreover, they provide vantage points for obtaining a clear view of damages (Fig. 1d–f).

Machine learning (ML) technologies, particularly in computer vision for SHM of heritage structures [7–10] are transforming CH inspections and are useful to heritage professionals. The use of computer vision (CV) technologies, particularly deep learning (DL), can considerably increase the accuracy of damage detection on images of CH structures and detect damages that are not visible by traditional visual inspections, allowing them to mark them as visible defects. In this regard, artificial-intelligence (AI)-assisted visual

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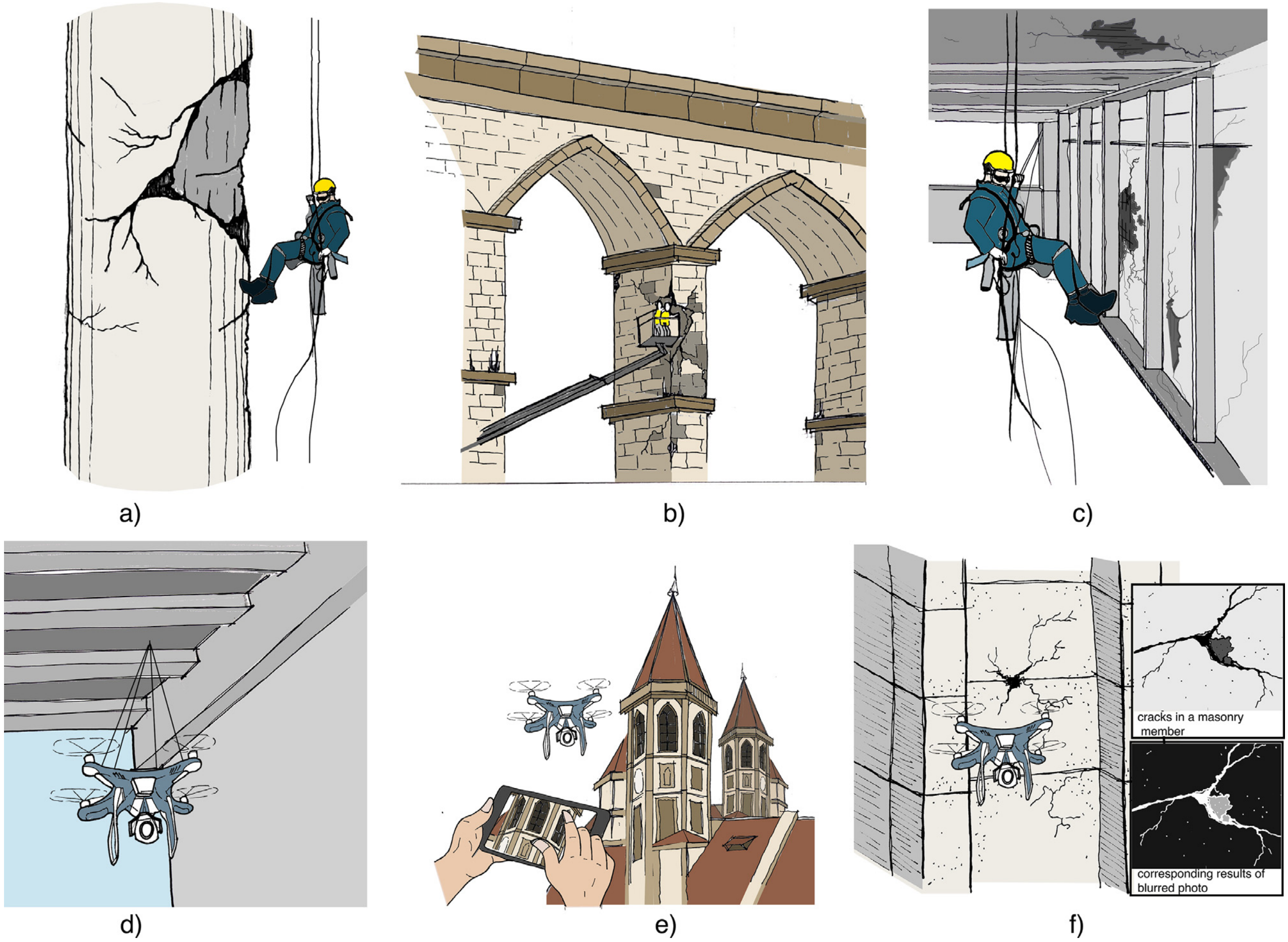


Fig. 1. Problems with traditional visual inspections: a–c) hard-to-reach places (adapted from Jungert [2] and Ciampa et al. [3]) and high-risk locations (modified from Pham and La [4]), d–f) drone-based inspections with an interface to watch the footage in real-time (Figures adapted from Otero and Gagliardo [5] and Li and Liu [6]).

inspection is useful to inspection professionals involved in the traditional visual inspection of CH structures and can help in maintenance decisions. AI-assisted inspection uses technologies that are mainly CV-based and examine and interpret digital image data to detect anomalies [11,12]. AI systems can be trained to recognize specific objects or features in CH images or drone footage, such as cracks, spalling, and efflorescence, from digital data. By identifying and pinpointing damaged locations early, maintenance can be carried out before expensive repairs are needed or safety is compromised. Thus, there is a growing emphasis on improving inspection speed and digitizing inspections carried out for future reference, thereby utilizing the best practices of humans and machines for saving CH structures. Furthermore, AI-assisted inspection analyzes digital images for locating possible defects in images, and inspection professionals who were not present at the site can later provide guidance or recommendations to human inspectors based on their expertise in analyzing defects by AI.

Inspection and industry-specific needs for different structures vary, for example, discoloration of stones may decrease the touristic value of CH. Damages on the surfaces of CH structures, such as material deterioration, vegetation, and discoloration, are likely to significantly impact the aging of the structure and aesthetic value in the long run. CH sites, like any other infrastructures, are susceptible to damage, which can harm their integrity and functional use if not repaired in a timely manner. To address CH structural assessment, several modern methodologies are deployed for inspection, in addition to traditional non-destructive techniques [13–17]. In this regard, digital image processing (DIP) involves the processing and analysis of image data to access information regarding surface-related damages, degradations, and imperfections in CH buildings. DIP techniques are non-destructive and conform to the ICOMOS guidelines [18] for non-invasive inspection. Additionally, images of CH buildings can serve as digital maintenance records and can be used as a baseline for comparison in the future. Moreover, drone-captured images and videos of inaccessible locations of CH sites can be analyzed by inspection professionals without risking their safety by accessing dangerous locations.

Deep learning-assisted visual inspection systems are gaining popularity for inspecting bridges [19–23] and roads [24–27], as well as, in the construction industry [28–30] and modern concrete buildings and concrete surfaces [31–34]. They can assist inspection professionals by detecting damages and bounding boxes pinpointing using object detection algorithms. As mentioned, they provide a digital record of current damages and their propagation over time, in addition to monitoring their severity in subsequent inspections. Concrete databases of cracks and bridge inspection systems are well-established and have been successfully applied, with promising results in the damage detection for these typologies. The review work has already been well-established for concrete buildings; however, for CH, relevant studies need to be summarized.

This review comprehensively describes the published case studies assessing surface damage in CH and other structures using DL-based methods. In addition, it discusses the advantages and limitations of these methods.

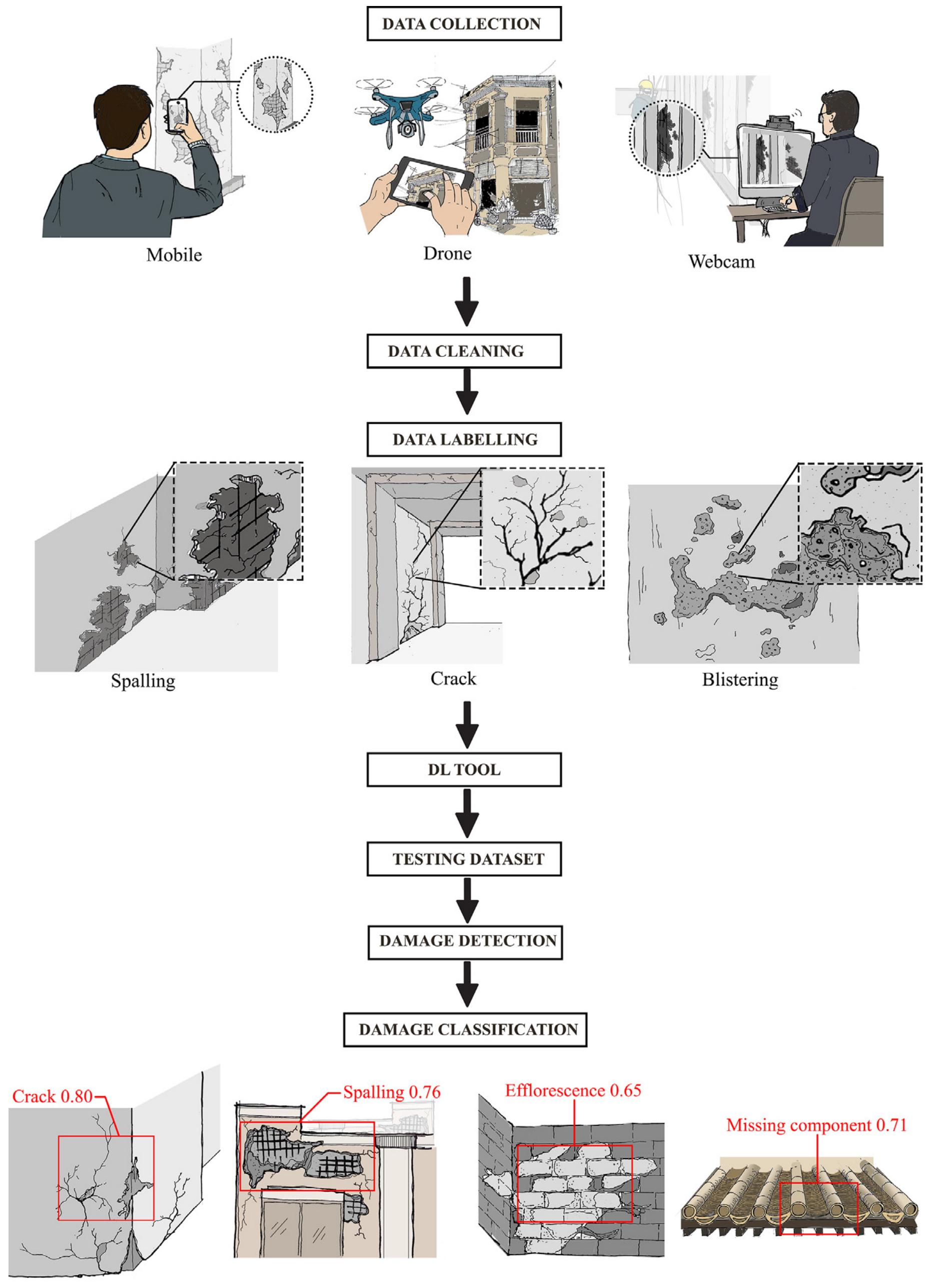


Fig. 2. Flowchart of AI-assisted inspection process (Sub figures adapted from Zou et al. [35], Li and Liu [6], Mansuri and Patel [36], Mishra et al. [37] and Wang et al. [38,39]).

2. Background information

The methodology for applying an AI-based approach to assist visual inspections is using a DL-framework model, primarily a convolutional neural network (CNN). Fig. 2 refers to the series of steps that are used for the AI-based visual inspection model. In the first step (data collection), data from CH structure is collected from either a mobile phone, camera, drone, or webcam and is passed onto the next step of data cleaning. In the field, site data collection is paramount because when we learn from the data and its interpretation from experts, then only we will develop an "expert system based on AI" giving the right predictions. Data cleaning refers to removing bad-quality data from the database, and then labeling is performed by expert operators to classify typologies of defects so that the DL model can be trained with the knowledge of experts. Even if the CH images are available, it is important to have images in an annotated version. An annotated dataset is essential as it saves lots of time, and other researchers do not have to go through each image and label them for defects. They can merge their annotated dataset with the annotated dataset made available publicly without having to go through the tedious procedure of labeling again. Even in data availability, they can share the annotated version of the dataset instead of just images to make their data usable for the scientific community. Most of the data collected is not for the purpose of training deep-learning models, hence it becomes difficult to utilize them at full capacity, and in this case, only a fraction of images can be used for the DL models. Hence, a framework to collect data specific to train DL models should be in mind instead of data collected for other purposes and then improvised to use for DL models. In some cases, the dataset is augmented by rotation of images, adjusting the contrast/brightness of images, and in general, performing operations such as flipping to generate more

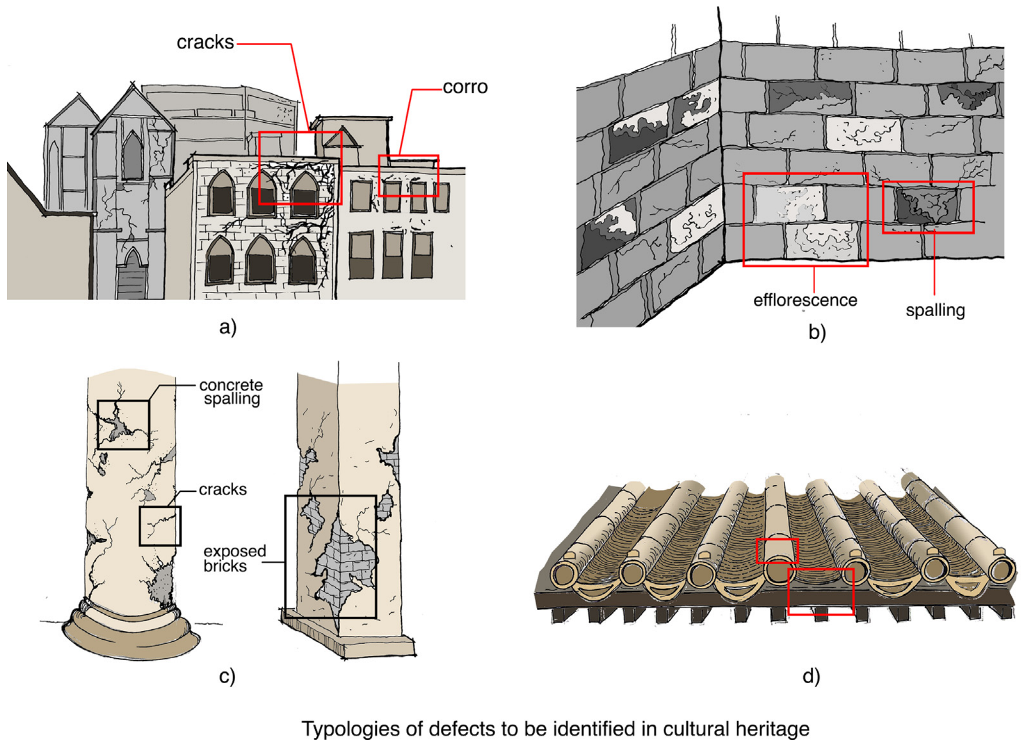


Fig. 3. Examples of application of DL-based deterioration detection in CH structures: a) damage typology identification, b) efflorescence and spalling damages in brick-mortar masonry (adapted from Wang et al. [38,39], c) damages in masonry columns (spalling, exposed bricks and cracks) (redrawn from Mansuri and Patel [36]), and d) missing components (redrawn from Zou et al. [35]).

images from the parent image. Some databases of images related to earthquake-related damages could be used for model training as they represent a vast collection of damaged buildings. In this regard, Kamel et al. [40] "crowdsourcing recommendation model" could be used for annotation of CH images retrieved from open access platforms and social networks such as Facebook and based on the user's description of the image (e.g. Facebook caption/social media post description by the user/comments) as a new technology to best match the annotation recommendations and assist in CH preservation.

Once the DL model is trained on the test dataset, then unknown data is presented to it for damage classification, and it classifies the unknown data into various typologies of damages such as cracks, spalling, efflorescence, and missing components in the CH building, as shown in the last step of Fig. 2.

Tables 1–6 presented in the review below mention DL-technique used by several types of researchers in their CH damage detection on images applications, out of which most common ones are, you only look once (YOLO) [41], region-based convolutional neural networks (RCNN) [42], Faster RCNN [43], Mask R-CNN [44], etc. The preferred one recently used in CH applications is YOLO, as its magnitude times faster than Faster R-CNN and being a single stage detector, it can predict at once the bounding boxes for CH defects and the class probabilities for these boxes having CH defect typology. Faster RCNN can detect small damage typologies, which YOLO can miss in detection, but RCNN cannot be deployed for real-time video feed from damaged CH sites owing to its two-step architecture. The performance evaluation of DL models is done through several indicators and performance metrics reported in the last columns of Tables 1–6 such as average precision (AP), F1 score, recall, confidence score, accuracy, intersection over union (IoU) and mean average precision (mAP) whose formulations and details can be referred to in several researches [45–47].

3. Applications of AI-based inspection methods in CH

Several studies have focused on surface damage detection of CH structures. In these studies, researchers have used object detection algorithms to identify damages that are visible on the surfaces of CH buildings. Damage pathologies in CH structures are classified and localized using bounding boxes into assigned category classifications. The same approach was also validated using post-disaster reconnaissance data of the CH structures captured after an earthquake. Fig. 3 illustrates some of the applications where DL-based inspection process in CH has been deployed.

3.1. AI-assisted detection of surface deterioration in CH and its applications

In this section, research on surface deterioration typologies using AI frameworks that are typically used for CH structures is reviewed. Some damages do not pose an immediate risk to CH structures, but they can be catastrophic in the long run. Some damages can also decrease the aesthetic value of CH structures.

Mishra et al. [37] applied a DL framework, namely You Only Look Once (YOLO; v5), which is a real-time object detection algorithm, and a faster R-CNN, to study a monument in New Delhi, India, for detecting four types of defects, namely, discoloration, exposed bricks, cracks, and spalling (Fig. 4a). The applied DL framework can be extended to other monuments by training the network on more damage typologies. Mansuri and Patel [36,48] developed an automatic web-based visual inspection system using a DL framework named faster R-CNN for detecting three classes of defects on a case study monument in Surat, India. Wang et al. [49] used a DL framework to detect several types of damages (spall, crack, and efflorescence) in masonry CH for Beijing's Forbidden City wall structure, with an average accuracy of $\geq$ 94.3%.

Table 1
Review of various case studies utilizing DL for surface deterioration detection in CH structures.

Reference	case study	dataset size	DL-technique used	Typologies detected	Accuracy/mAP/recall
[37]	Dadi-Poti tombs in New Delhi India	10291 images	YOLOv5 and faster R-CNN	discoloration, exposed bricks, cracks, and spalling	93.7%
[36,48]	English and Dutch cemeteries in Surat India	880 images	faster R-CNN	spalling, exposed bricks and cracks	91.5%
[49]	Forbidden City Wall in China	2400–24000	sliding window-based CNN	intact, crack, efflorescence, spalling	94.3%
[39]	Palace Museum wall and moat wall in China	500 images generated from two orthophotos	faster R-CNN	efflorescence and spalling in masonry structures	95%
[38]	Great Wall of China	610 images	GreatWatcher platform based on R-CNN	four damage classes employed were intact, crack, efflorescence, spalling	78.2%
[50]	Kasbah of Algiers	2674 images	CNN (mobileNetV2 with a transfer learning approach)	Efflorescence, spalling, crack, mold	86.8%
[51]	two different types of marquetry with CH elements	two thermal images of Marquetry with surface defects	Mask Region-Convolution Neural Network (Mask R-CNN)	surface defects, honeycombing, missing tesserae, subsurface defects	97.1%
[52]	Ayutthaya Wat Phra Si Sanphet Temple, Thailand	7500 high-resolution images	Faster-RCNN	crack, spalling	crack = 25.4%- 44.6%, spalling=52.4%-71.8%)
[53]	CH in Macau	1355 photographs	YOLOv4	five types of damage: missing, cracking, plant or microbial erosion, yellowing, and pollution	85.7%
[54]	heterogeneous dataset of images of historic buildings	moist area (173 images), Biological colonization (100 images)	Mask R-CNN	decay mapping of some particular classes of alterations (moist area, biological colonization)	0.74- 0.80
[55]	Historical bridges in Isfahan	8331 images	Inception-ResNet-v2	cracking, flaking, erosion, salt efflorescence, and no defect	96.6%
[56]	real existing RC heritage bridge in Southern Italy	10779 labeled images	eight CNN models	cracks, corroded steel reinforcements, deteriorated concrete, honeycombs, moisture spots, pavement degradation, shrinkage cracks	best one 63.5%
[57]	various heritage buildings in India	4500 images	CNN and support vector machine (SVM)	five classes of degree of damages in CH	80.2%, 85.6%

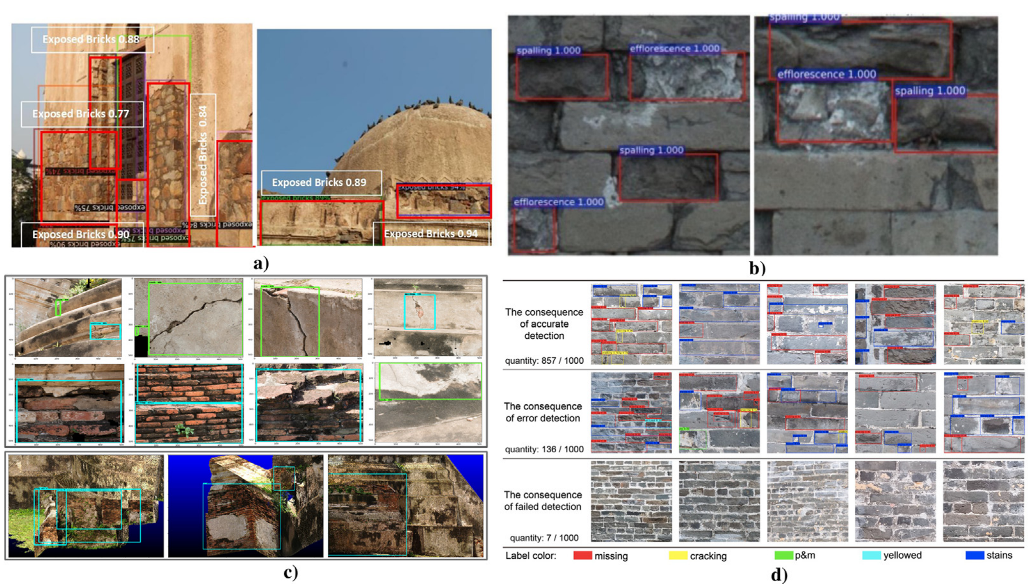


Fig. 4. Examples of AI-assisted visual inspection systems for surface defects: a) employing YOLO for detecting surface damages in Dadi-Poti case study [37], b) detecting damages for efflorescence and spalling [39], c) Faster R-CNN model for detecting spalling (light blue bounding box) and cracks (light green bounding box) [52], d) categorizing five types of damages for CH in Macau [53].

Table 2
Literature review on the use of DL for façade and masonry walls damage detection in CH structures.

Reference	Case study	Dataset size	DL-technique used	Typologies detected	Accuracy/mAP/Recall
[58]	Lasem district in Indonesia	260 images	CNN with transfer learning	4 classifications (good, lightly damaged, moderately damaged, severely damaged)	60.0%
[59]	CH building in Jordan	1024 images	CNN	erosion, material loss, color change of the stone, and sabotage issues in CH	95.0-96.0%
[60]	images of building façades	1907 images	several versions of YOLOv7	Three namely, delamination, spalling, tile loss	77.6%-81.6%
[61]	external wall tile images	5680 images for training dataset	pretrained CNN VGG-16 classifier	efflorescence, spalling, cracking, and defacement	91%, 100%, 86%, 98%
[62]	façade images of public residential buildings in Singapore	2055 images	basic Mask R-CNN model optimized by the designed rules	spalling, crack, biological growth, blistering, peeling	localization= 0.51-0.65 and segmentation= 0.46-0.58
[63]	Loire valley, France	1012 color images	deep learning architecture, using YOLOv5 and transformers	spalling deterioration	81%,
[64]	masonry wall images from UK	351 photos containing cracks and 118 without crack	CNNs pretrained on ImageNet	Two (crack, no-crack)	95.3%
[65]	images of brick walls built in a laboratory environment	2542 labeled image patches	convolutional neural network (CNN)	cracks in images of brick-and-mortar structures (both lab and real-world)	88.7% - 92.5%
[66]	Spain, specifically in Andalusia	765 images (4704 bricks labels)	Yolov5 DL-framework	efflorescence	0.89
[67]	some internet and some self-captured	107 images of masonry structures	U-Net, DeepLabV3+, U-Net (SM), LinkNet (SM), and FPN (SM)	Two (crack, no-crack)	96.86%

Table 3
Review of the literature on the use of the DL for cracks damages in CH.

Reference	case study	dataset size	DL-technique used	Typologies detected	Accuracy/mAP/Recall/F1 metric
[68]	Royal Exhibition Building in Melbourne, Australia	71142 crack and 100200 no-crack images)	ReCRNet	cracks, no-crack	92.3%
[69]	synthetic images	3000 image pairs	Siames CNN	8 crack-patterns without opening	R^2 = 0.51 - 0.74
[70]	EXPE and WILD dataset from EPFL	301 training, 129 validation and 100 test patches (EXPE) and WILD(5360 training, 1287 validation and 533 test patches),	DL-framework TernausNet	crack patches	F1 metric = EXPE (76.5%), WILD (68.5%)
[71]	Historic sites in Bhubaneswar India	4000 annotated images	YOLOv5	two (crack, no crack)	92%
[72]	Historic City of Ayutthaya in Thailand	6002 picture patches	deep CNNs and SVMs	cracks and non-cracks	86%
[73]	external façade of the Architecture School of the University of Strathclyde, Glasgow	700 images	CNN (MobileNetV2, InceptionResNetV2, Xception)	crack or non-crack classes	upto 100%
[74]	timber structures of ancient CH of Shen-yang Jianzhu University	474 pictures	YOLO v3, v4s-mish, v5s	cracks	92.9%

Table 1 summarizes the work done by several researchers, along with the datasets used, the DL models used, and the types of damages identified. Wang et al. [39] used a DL-based CNN for detecting damages in brick masonry for a palace wall in China (Fig. 4b) and later used the system for web-based monitoring and mobile-based detection system using video feeds from the structure. In another research, Wang et al. [38] combined DL with mobile crowd sensing (MCS) techniques to automatically analyze damage to the Great Wall CH in China. Meklati et al. [50] proposed a crowd-sensing solution based on DL-frameworks to estimate deterioration and loss in CH. The proposed mobile application can be used by CH inspectors, wherein they can capture pictures of suspected damaged walls and immediately assess damaged areas through the embedded CNN. Garrido et al. [51] employed infrared thermography instead of direct image data and used a thermal image of CH to detect five classes of defect positions from the background in two different types of marquetry. Pathak et al. [52] considered the two most common damages in CH structure, namely, cracks and spalling from the Hampi heritage site in India (Fig. 4c) for detection of damages in images and further devised preservation plans. Researchers have used damage detection locations on 2D images, but they have been able to locate these in 3D rendered projections assembled through point-cloud data. Yang et al. [53] employed a YOLOv4 DL-model to automatically detect five types of damages,

Table 4
Review of the literature on the use of the DL for stone CH.

Reference	case study	dataset size	DL-technique used	Typologies detected	Accuracy/mAP/Recall /confidence score
[75]	Stone dataset from the regular report of the National designated CH property	100 pieces were extracted for each type of damage from 3335 images	Faster R- CNN	crack, material loss, detachment of material, biological colonization	94.6%
[76]	Stone CH in Konya region	8598 images	ANN and three-layer CNN	nine defect classes (fresh rock, flaking, contour scaling, cracking, differential erosion, black crust, efflorescence, higher plants, and graffiti)	94.0% and 99.4%,
[77]	Yazlkaya monuments in the Hattusa archeological site	2460 images	Mask R-CNN	deteriorations (biological colonization, contour scaling, crack, higher plant, impact damage, microkarst, missing part)	89.6% -100%
[78]	Château de Chaumont in the Loire Valley (France)	1000 high resolution images	YOLO network (YOLOv5 incorporating transformer)	spalling zones in limestone walls	about 79%
[79]	Konya, Turkey	1800 images collected from nine historic buildings	Mask RCNN	Seven different lithologies (Gödene stone, pink dacite, gray dacite, pyroclastic rocks, marble, basalt, and mudstone)	89.1% -100%

Table 5
Review of the literature on the use of the DL for components detection in CH.

Reference	case study	dataset size	DL-technique used	Typologies detected	Accuracy/mAP/recall /precision
[80]	Architectural heritage elements dataset	500 images	pre-trained CNN (GoogLeNet, resnet18 and resnet50)	10 elements (altar, apse, bell tower, column, dome (inner, outer), flying buttress, gargoyle, stained glass, vault)	87.9%, 95.5%, 95.6%
[81]	monument façades of MonuMAI dataset	514 RGB images	CNNs (faster R-CNN and ResNet-101)	fifteen key architectural elements	0.60
[82]	various architectural heritage images	8624 images	CNNs	ten categories in particular bell tower, stained glass, vault, column, outer dome, altar, apse, inner dome, (ix) flying buttress, gargoyle	90%
[83]	Victoria Gallery and museum in Liverpool UK	2400 infrared thermal images	CNN	8 classes (doors, artwork, arches, vents, windows, stonewall, brick wall, and cracks)	97.72%
[84]	heritage buildings of India	3000 heritage buildings image	enhanced ET-YOLOV5	gateways in historical buildings	88%
[35]	Forbidden City in China	162-435 images	Faster R-CNN	missing components in CH	0.75-0.91
[85]	crowdsourced images from Scotland	113 photographs	DeeplabV3 segmentation models	seven classes (window, sky, plant, masonry, hole, gate, signboard) and then regions of biological growth	84.4%
[86]	92 CH sites around the world	thousands of images from social media and internet	CNN	Heritage, no- Heritage then (no-damage, damage), then earthquake affected damages	0.91-0.94

namely, missing paint and bricks, stains and yellowish bricks, plantations, and cracks to historical CH structures in Macau (Fig. 4d). Many of the damage types are not harmful to the structural integrity of CH; however, because of climate variations, they may be harmful later, and thus, they should be identified in time to enable conservation work. Bruno et al. [54] proposed a mask R-CNN model to detect decay morphologies on built CH as a support system for conservation professionals by providing preliminary knowledge about the building state of conservation. Recently, Karimi et al. [55] applied an inception-resnet model to detect several damage typologies such as cracks, flaking, erosion, and effervescence on a bridge CH structure and demonstrated that even a single technique like taking pictures using mobile cameras can assist the defect detection process in CH bridges and can be easily extended to other structures worldwide. The model deployed by Karimi et al. [55] achieved an accuracy of 96.6%, precision of 97.0%, and recall of 96.2% for the identification of defects in two types of materials, and it can be expanded to several other case studies on bridge CH structures. In another research on bridges by Cardellicchio et al. [56], automatic recognition of defects on reinforced concrete (RC) bridges having CH value in Italy was carried out by deploying eight different CNNs using transfer learning starting from weights pre-trained on a DL-framework called ImageNet. This approach of transfer learning is beneficial as it is closer to real-life

Table 6
Miscellaneous applications of AI-assisted visual inspections for CH inspections.

Reference	case study	dataset size	DL-technique used	Typologies detected	Accuracy/mAP/recall
[87]	roof images of the Palace Museum in China	100 roof images	Faster R-CNN	four (simple, moderate, serious, severe)	0.89-0.91
[88]	STL-10 dataset	20 images x 7 classes	CNN	seven different classes of dust level (noise)	several probability scores for each CH building
[89]	historical temple in Bangkok, Thailand	3600 images	CNN	two (damaged and undamaged tiles patches)	95% (validation), 91% (testing)
[90]	Aged buildings across Taiwan	1458 images with 4595 tile-peeling instances	YOLOM model	tile-peeling instances	66.83%
[91]	photos taken by mobile phone	2622 images	pre-trained CNN classifier of VGG-16	four (mold, stain, paint deterioration, no defect)	87.5%
[92]	on-site Chinese clay tiles in Macau China	363 photographs	YOLOv4	3 damage typologies namely cracks, stains, surface wear	95.42%, 80.91%, 89.34%
[93]	monuments in Portugal	5000 images	CNN	4 damage typologies namely cracks, crater, glaze detachment, tile lacunae	Not available
[94]	grottoes mural datasets	277 mural pictures	Ghost-C_3SE YOLOv5	minor cracks and small fall off areas	56.7%
[95]	Xanten Cathedral	4000 photos of mold in CH	CNN	mold defect	97%
[96]	Palace Museum, Beijing	600 images	semantic segmentation method (Res-UNet)	Craquelure and paint-loss defect in paintings	98.2%

inspections, where inspection professionals use knowledge from past inspections to enable decision-making. A study by Mehta et al. [57] applied DL for classifying the severity of damage in CH buildings, ranging from severity level 0 (No visible damage) to severity level 3 (severe damage (e.g., collapsed walls, significant structural damage). The study when compared to other studies gave an overall evaluation of the CH building instead of just pinpointing damages and hence is essential for prioritizing repairs and maintenance.

Based on the literature review, it can be concluded that surface-related damages can be monitored using DL/AI techniques and serve as a digital record for aiding in the preservation process, especially in cases of CH preservation with long timelines and different inspectors; thus, digital records of damages are essential. Based on the review of DL/AI for surface deterioration detection, the studies by the following [36,37,39,48–50,52–54,56] went a stage further to "pin-point" the exact location of damages along with their typologies, while other researches [55,57] focused on only identifying if the damage typology is present or not in the CH image inputted to the model. Notably, a few of them [37] used DL frameworks like YOLO capable of real-time assessment (capable of processing frame rates compatible with video feeds), which in the future could be integrated with drone footage video feeds.. Additionally, one select publication, [57], gave an overall global perspective on the damaged building condition instead of just locating the several damaged regions and letting the inspection professional decide regarding the current health status of the CH building. Furthermore, digital images can help pinpoint damaged areas and serve as a starting point to implement more in-depth complementary techniques such as laser scanning, infrared thermography, or sonic tests.

3.2. AI-assisted recognition of façade damages in CH

Some recent studies have assessed the level of damage in CH buildings façades using AI-based techniques, summarized in Table 2. CH inspections, especially of their façades, are critical to ensure public safety and aesthetics, and AI-driven inspection of façades can help in spotting damages in time. Dini et al. [58] trained a DL model on 260 images of historic CH façades and achieved an accuracy of 60.0% for identifying damage classification. Samhouri et al. [59] selected the city of "Al-Salt" in Jordan to identify common façade damages due to erosion, material loss, color change of the stone, and sabotage (Fig. 5a) in CH façades using CNN. Wei et al. [60] used DL-model named YOLOv7 and its improved versions for façade defects such as delamination, spalling, and tile loss in old buildings and their works be expanded to CH buildings as many defects are common to CH typologies. A major advantage of YOLO being used in this study is that it meets real-time prediction capabilities (in this case frames per second of 76), which many CH DL models do not meet. Similarly, Kung et al. [61] deployed fine-tuned transfer learning to an ImageNet-pretrained VGG-16 network with UAV data to defect four defects namely efflorescence, spalling, cracking, and defacement in external building tiles of façades with good accuracy for various defects individually reported in Table 2. Guo et al. [62] used rule-based DL for detecting façade defects. They focused on detecting damage type (mainly cracks and delamination as shown in Fig. 5c), location, number, and size of façade defects based on industry standards rather than focusing only on achieving high accuracy. Another common deterioration pathology, namely spalling in stone CH buildings, was identified using YOLO by Idjaton et al. [63] for limestone masonry castles in the Loire Valley structure. The inference time required was approximately 1 min for the DL framework, achieving an average accuracy of $\geq$ 80% (Fig. 5e, first row), however, there found some incorrect predictions owing to tiny degradations which are not recognized even by visual inspections (Fig. 5e, second row). This approach can help cultural heritage experts save time and increase confidence levels in their structural health assessments.

Apart from façade damages, there are several applications of DL in damage detection of masonry walls that can be applied for CH structures. Dais et al. [64] investigated the performance of DL-based techniques to detect cracks in masonry walls (Fig. 5b) at both patch and pixel levels. They concluded that the detection ability of cracks increased by adopting transfer learning. Hallee et al. [65] trained CNN on images of brick-and-mortar walls built in a laboratory environment and tested their model in the real-world to test its applicability for identifying cracks in situ. Marín-García et al. [66] used DL to detect only efflorescence as a common dam-

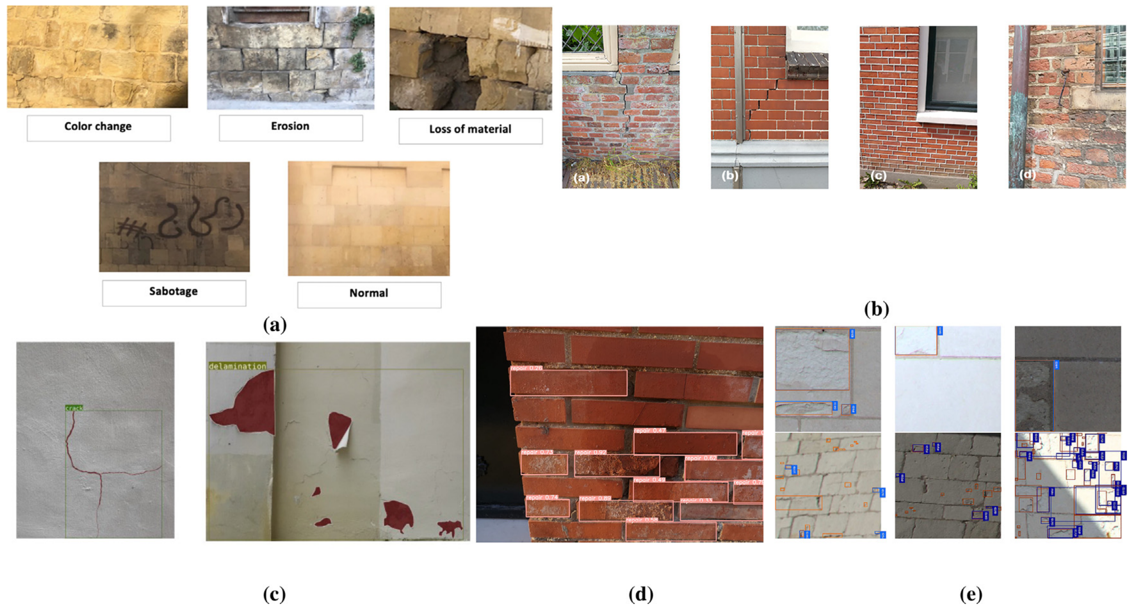


Fig. 5. a) CNN deployed by Samhouri et al. [59] for façade damages in "Al-Salt" in Jordan, b) masonry surface defects considered by Dais et al. [64], c) sample façade defects (e.g. crack and delamination) [62], d) AI-system for façade bricks to indicate need to clean or repair [66] (red bounding box and red text showing repair label), e) correct (first row) and incorrect (second row) AI-assisted models results for tiny degradation on surfaces [63] (red bounding box showing predictions with confidence score in blue text).

age pathology in façade bricks and judgment if the façade needs cleaning or repair (Fig. 5d).

Based on the review, only the research paper by Dini et al. [58] provided a global assessment of façade condition in terms of a unique condition score, while others [59–63] mainly focused on pinpointing damage typologies such as erosion, color change, spalling, cracks, etc and based on the identification inspection professionals can decide about the interventions. Furthermore, researches [64–67] evaluating cracks in brick-and-mortar can also be extended for CH facade are also listed.

3.3. Crack detection using AI in CH

AI-assisted inspections have proven promising and can be for locating cracks in CH buildings whose applications are summarized in Table 3. Reis and Khoshelham [68] developed a DL framework called ReCRNet for crack detection in historical buildings (Fig. 6a). The model was tested on two image datasets, a normal and a larger set, by augmenting the normal dataset (from 171 to 342), and achieved an accuracy of more than 90% to identify cracks. In an ancient CH structure, Rozsas et al. [69] used Siamese CNNs (SCNNs) on synthetic image data whose input was two crack-pattern images; the output was similar in crack-pattern images that can relate to actual condition assessment by structural engineers. Pantoja-Rosero et al. [70] presented a novel method to segment cracks in masonry buildings in general, although they did not directly deal with CH stock that was affected by the earthquake. In another recent application of crack monitoring using AI, Pratibha et al. [71] used an automated YOLOv5 version to pinpoint the location of cracks in masonry structures (Fig. 6b) with a database collected from historic sites in Bhubaneswar, India. This study helped structural engineers adopt second-stage repair procedures to fill cracks using epoxy resin or other appropriate techniques. Ravichand et al. [72] adopted a combination of drone and camera to capture photos and used an integrated CNN-support vector machine (SVM) model to automatically detect cracks on masonry photographs. Katsigiannis et al. [73] deployed "Building Façade Defect Inspection" model for crack detection on brickwork masonry façades using transfer learning with limited annotated data. Although not directly related to CH, the crack or non-crack classes are common to CH structures, and the model can be extended to CH structures. Loverdos and Sarhosis [67] used various DL techniques for crack detection of masonry walls and highlighted the potential of DL technology for digital documentation of stone masonry damages. Ma et al. [74] did one of the first studies where the DL framework YOLO was applied to intelligently detect cracks in timber elements of the ancient architecture. The applications highlighted in this section focus on identifying cracks in structural members [67–73] and ancient timber structures [74]. Some applications do exist in crack detection for "non-structural members" such as tiles of the roof, façade, and floor as summarized later in Section 3.6. Thus, the review is relevant for crack detection and monitoring using digital technologies and can assist in CH preservation.

3.4. Degradation monitoring of stone CH using AI

Stone CH is no exception to degradation and can lose its aesthetic value and suffer considerable damage with time. AI-assisted techniques have been applied in degradation monitoring of stone CH structures. Kwon et al. [75] used faster R-CNN to detect four types of damages (crack, loss, detachment, and biological colonization). They also used image augmentation techniques such as 90° rotation, flipping images upside down, left-right reversal, changing image settings such as brightness, darkness, and sharpening on the original dataset, and increasing the dataset size to sevenfold, achieving an improved model score of approximately 17.5%. Hatir et al. [76] determined the extent of weathering in stone CH structures using DL, which is one of the most common damage phenomena observed in stone. They categorized eight types of weathering damage, namely, cracking, fresh rock, graffiti, differential erosion, black crust, contour scaling, efflorescence, and vegetation, which are typical to stone CH structures in 11 different studies in the Konya region, in Turkey. In another study by the same authors, Hatir et al. [77], on a UNESCO CH site in Yazlkaya Turkey, mask R-CNN-based algorithm models were tested for damage identification. They concluded that the deterioration via AI technique, although applied to a specific region, can be applied to more stone

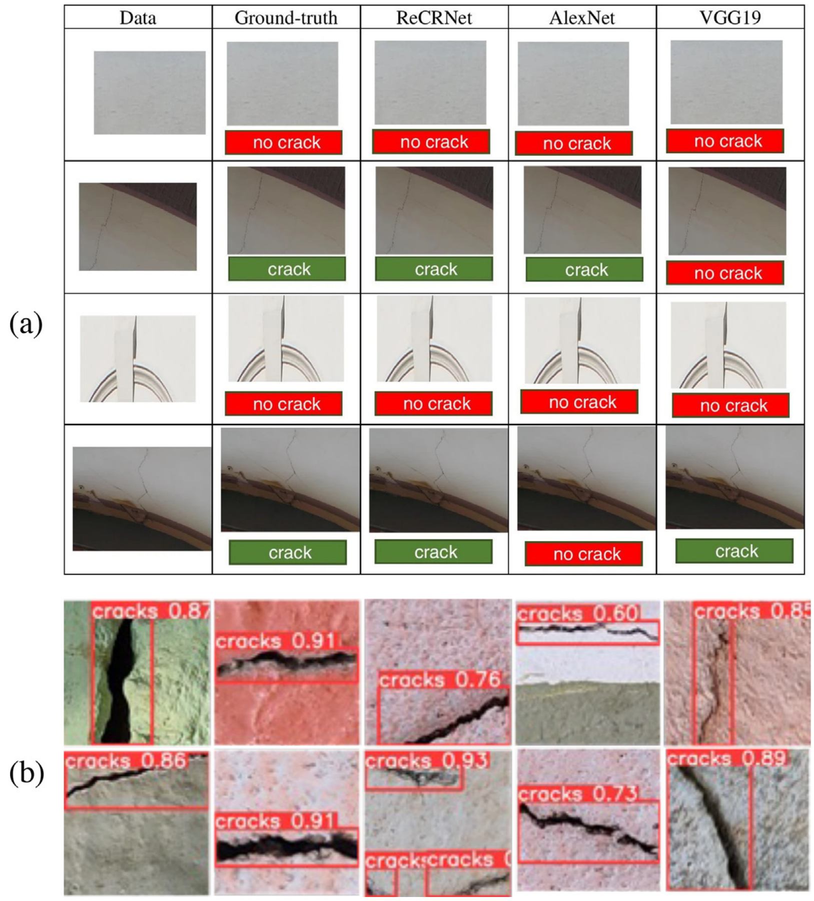


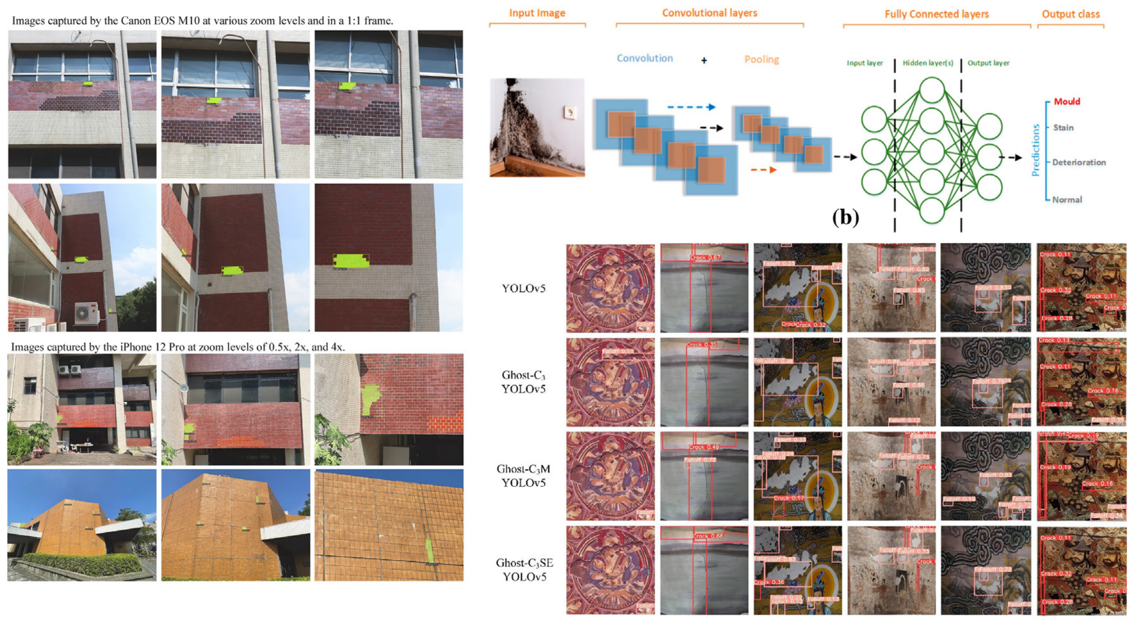
Fig. 6. a) An AI-based tool named ReCRNet deployed by Reis and Khoshelham [68] for crack detection in CH buildings, b) YOLO-based DL-model for detecting cracks in CH buildings in Bhubaneswar India [71].

heritage sites worldwide based on images captured using mobile cameras, drones, and computer applications for analyzing image data for possible signs of damage. Idjaton et al. [78] used the YOLO object detection model to automatically detect spalling zones in limestone walls. In another study by Hatir and Ince [79], the DL technique mask RCNN was used for determining building stone lithology in Konya, because the determination of building stone lithology is essential for carrying out conservation works to replace damaged stones in CH structures. Table 4 summarizes such applications, where DL has been used for detecting deterioration of stone CH structures.

3.5. Components and key architectural elements detection in CH using AI

The extraction of key architectural elements and components in CH buildings is essential for the conservation process and enhances the digital documentation process. Several studies have employed DL to facilitate the identification of CH elements, as the images are not taken by professionals and are not captioned in most instances. Abed at al. [80] reused pre-trained CNNs utilizing transfer learning of the model instead of random weights on the Architectural Heritage Elements dataset (AHE_dataset), which was further divided into three versions based on the number and size of images. The classification results using ResNet-18 produced better classification results compared with other pre-trained CNN. Lamos et al. [81] pointed out that the use of DL in identifying CH knowledge in art and history is beneficial, but it can also provide deep insights into the state of conservation of CH. The authors introduced a Monument with Mathematics and Artificial Intelligence (MonuMAI) framework based on DL for detecting architectural elements and architectural style classification in CH buildings from façade images, which is mainly associated with experts only. Cosovic et al. [82] utilized a DL-framework on CH images to classify them into 10 categories, achieving an accuracy of 90.0%. Seo et al. [83] classification using CNN on multi-category thermal images instead of direct images for damage detection in CH buildings. The authors collected a total of 2400 infrared thermal images and annotated the images for 8 labels such as doors, artwork, arches, vents, windows, stonewalls, brick walls, and cracks. Another component in CH buildings is gateways which were detected using an enhanced version of YOLOV5 by Chawla et al. [84]. Instead of components, Zou et al. [35] identified missing components in CH buildings using CV based on a CNN framework, thus paving the way for intelligent inspection systems to assist in traditional visual inspections.

Previous researches [35,80–84] highlighted in this section focused mainly on identifying the components and elements of the CH building without any indication of damages present in them. The research highlighted in this paragraph [85,86] went a step further, and after identifying the CH component, detected agents causing surface-related damages such as plants [85], and whether the component is intact or not [86]. Liu et al. [85] relied on information from crowdsourced images to monitor CH sites by deploying a combination of semantic image segmentation and photogrammetry. First, a one-stage model was applied to segment seven classes; then, a two-stage model was used to segment the results into binary classes, allowing measurement of the area of biological growth. Although the paper only tackled plant growth, the potential applications include monitoring cracks and erosion



(a) (b) (c)

Fig. 7. a) Detection of tile peeling using YOLOM for images captured using camera and iPhone at various zoom levels [90], b) DL-model used for mould, deterioration, and stain detection for buildings [91], c) damage detection results for murals (boxes show confidence values for cracks (dark red) and fall-off (light red)) [94].

for CH prevention. Kumar et al. [86] also relied on crowdsourced images first to classify whether buildings are CH, and then, in the second stage, identified whether the ones identified as CH structures are intact. The method helped in degradation detection on images of CH sites, especially during disasters, and thus helped the conservation process. Thus, if the DL framework can detect intact and impaired components, it can promote the intelligent development of routine inspections of CH buildings. Table 5 summarizes contemporary literature for the detection of components and architectural elements in CH structures with details such as the location of the CH site, dataset size, DL-technique, classes detected, and the key performance indicators used for evaluating the results.

3.6. Miscellaneous applications of AI-assisted inspections

Apart from several direct structural monitoring applications of AI-assisted visual inspections, there exist several applications in literature where AI can assist in damage detection on non-structural components of CH structures, summarized in Table 6. CH AI systems can flag any anomalies detected in a CH structure based on input images. This includes damage in historic glazed tiles of roofs of Palace Museum in China [87], dust level in CH sites as an indicator for CH maintenance [88], tile-damages in temple façades [89], tile-peeling from UAV footages of building exteriors [90] (Fig. 7a), automatic detection of four key defects (mold, paint deterioration and, stains (model shown in Fig. 7b) [91], automatic detection of three typologies (cracking, stains, and surface wear) of defects in Chinese clay tiles based on YOLOv4 model with a frame rate of 30 photos/sec for practical applications [92], detection of tile defects such as cracking, craters, glaze detachment, tile lacunae in Portughese CH façades [93], identification of defects such as craquelure and paint loss in ancient paintings [91], damage detection of grotto murals [94] (Fig. 7c) and autonomous damage detection of mold in churches via using real-time mold cameras [95]. Robrecht et al. [95] also integrated IoT with CNN, which was pre-trained with 4000 photos of mold in cultural objects and used in the Xanten Cathedral case study, in Germany. Since mold growth is slow, 1 photo per night was captured over 5 months, thus effectively reducing the computational time. Yuan et al. [96] dealt with craquelure and paint loss defects that are typical in ancient polychrome paintings and decreased the aesthetic value of CH structure.

Furthermore, the earthquake-related damages and their AI-based assessment can be extended to CH structures. Mondal et al. [97] did not deal with CH structures directly, but the general buildings used for AI-based inspection in events of earthquakes to assess the integrity and autonomous damage assessment of CH general buildings. Mondal et al. [97] used DL to detect four different damage types, namely, cracks on surfaces, spalling of both façades, and spalling of concrete, and severe damage with exposed rebars and severely buckled rebars on input images collected from RC buildings damaged during previous earthquakes. Similarly, Ogunjinmi et al. [98] presented an AI-based system for damage assessment in the 2017 Pohang earthquake case study with samples divided into various damage classes ranging from no damage, light, moderate to severe damage classes. Xu et al. [99] utilized DL-framework (faster RCNN) to detect concrete cracking, spalling, rebar exposure, and rebar buckling from images of damaged reinforced concrete images in their study.

Cardellicchio et al. [100] deployed VULMA tool (VULnerability analysis using MAchine learning) [101] on existing building stock by exploiting image data of buildings downloaded from Google Street View to develop risk mitigation strategies, hence exploiting AI to retrieve information about building stock (masonry and reinforced concrete buildings). The authors concluded that AI-assisted objective detection methods could be deployed for future studies to reduce the burden on operators and automate several calculation modules. Masrour et al. [102] proposed DCNN models with transfer learning for the detection of seven classes of old building damages in a Morocco case study. Although their study was focused on old building damage pathologies, it can be extended to CH buildings as many pathologies are common to old buildings and CH stock. These miscellaneous applications summarize the other areas where AI-based tools can be tapped and can aid inspection professionals in preserving CH.

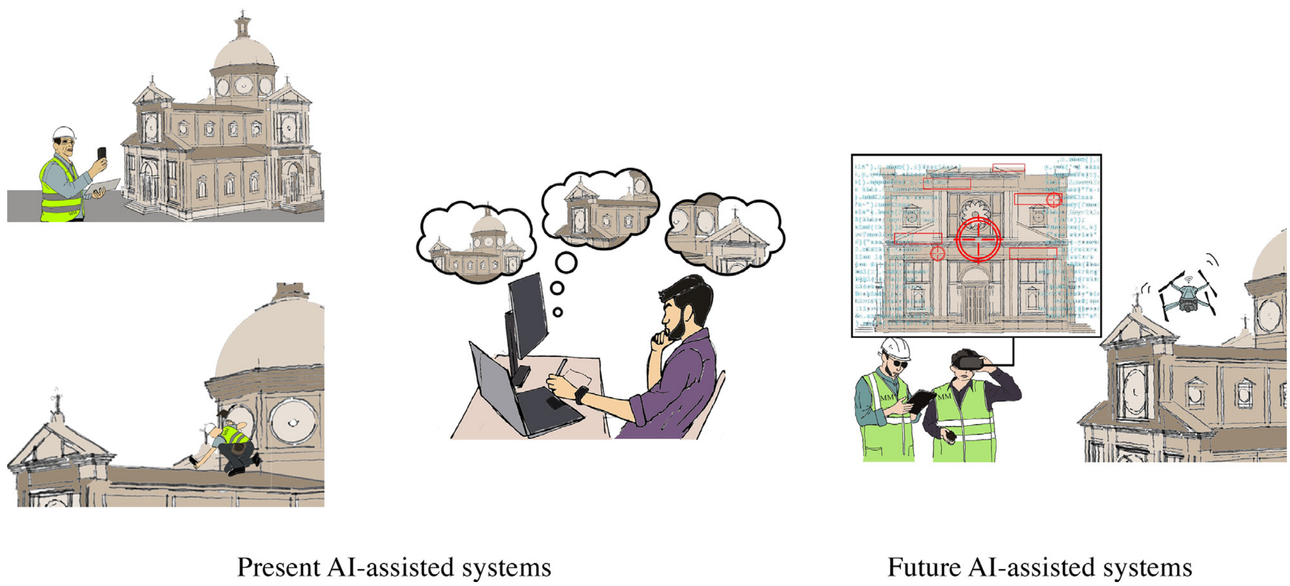


Fig. 8. Figure illustrating present to future AI-assisted systems for CH.

4. Limitations and future scope

This section discusses the potential application areas of AI in CH. In addition, challenges that can be encountered in AI applications, along with possible solutions to overcome them, are highlighted. Research is needed to fill the gaps in current visual inspection systems and move toward innovative inspection solutions such as integrating drone footage of video feed with AI models, advanced building inspection systems with integration of augmented reality (AR) [103] and real-time damage detection using internet-of-things (IoT)-based systems [104], thereby increasing the robustness of results and minimizing the processing times in DL models for identifying damages.

The AI approach is well suited to identify damages in CH structures because an AI model can learn from previous damage scenarios and train itself from the manually annotated damages of CH obtained by taking opinions from experts. However, it has some limitations, as the model depends on operator-dependent annotations/labeling (which could be addressed by employing multiple operators to reduce the biases), availability of large datasets for training/restricted sharing of datasets by researchers, training inspection experts to deploy models in their inspection routines, and availability of powerful machines with GPU processors to train/test models and one-size-fits-all models. For more details on data-related challenges, gaps, and their solutions in surface defect detection using DL, readers are directed to review the paper of Guo et al. [105]. Training of inspectors is essential so that they can be acquainted with AI-based inspection systems to supplement their damage identification procedures. The data that can be integrated with the DL-based model can vary from images from in-person and crowd-sourced image data to videos from drones and mobile cameras, which can be used for testing the model performance. The CH community needs to share their image databases so that others can use some typologies of damage to augment their data size and improve the accuracy of their models.

Research is needed, namely, for identifying minor damages, examining progression (with time) in various typologies of damages, and assessing the safety levels of CH buildings post-earthquakes. Furthermore, like in several deterioration detection based on images, the concept of transfer learning is being tapped in AI-based inspections, which needs to be implemented in current AI-based systems to improve their accuracy for CH inspection. The model can assist in case of earthquake events in judging if the building is safe to enter, by including damage markers such as pattern of cracks and damage severity. Future works need to be expanded to damage identification in disaster-hit areas, where, in many instances, inspection professionals take time to reach. Studies need to be carried out to develop more integrated AI-assisted inspection systems based on video feeds captured using IoT. As pointed out in the state-of-the-art, only one application exists [95] where IoT is integrated with an AI-assisted visual inspection system for mold detection in CH. Limited studies do exist in other fields such as Wang et al. [106] deployed the IoT framework for obtaining live feed of concrete surface samples after exposure to vibration for concrete consolidation. Similar to any AI expert system, it was trained using a surface image dataset of concrete vibration containing 15,000 images and expert opinions about the quality of vibration, such as unqualified, middle, and qualified, and this was used as a training set for the CNN model.

Engineers cannot sift through images, manually add them to the folders for testing, and then again run the code to see results in the input images and geotag them to the actual site. This, in reality, is not possible for them, and they need a trained, ready-to-deploy, and handy AI-based inspection tool at a site having a graphical user interface (GUI) that will be easily viewed on a screen during inspection (Fig. 8). The systems should be able to provide the "textual names or labels" of recognized damages (e.g., plaster cracking, structural cracks, peeling of paint, mold, wood rot, and biological damages). It will enable automatic inspections that can "geolocate" the damages, and there is no need for inputting the images one by one and again matching them with their locations in the CH structures (Fig. 8). This will save time and effort and eventually reduce errors.

Future research can also focus on detecting other damage categories in CH, such as algae growth, vegetation, and the presence of collapse mechanisms in CH, which have not been explored for DL-damage detection. The data can be coupled with laser scanning data to create a virtual reality/augmented reality walkthrough of the CH structure. Thus, a holistic approach can be realized by combining several techniques and intelligent AI algorithms to understand damage progression in CH structures.

5. Conclusions and discussion

The present review summarizes the studies on artificial intelligence (AI)-assisted inspections for damage detection of cultural heritage (CH) structures, along with several case study applications. Different deep learning (DL) techniques/object detection methods can be deployed for damage detection in CH. Computer vision (CV) technology supervised with expert feedback can be used to pinpoint damages on unseen image data, thus serving the purpose of a human operator. These AI technologies can be adopted to automate the inspection process for CH structures. The DL-based systems can be combined with virtual reality to train inspection professionals to identify damages. Furthermore, the inspection stages of the automatic inspection processes are digitized and saved in image data, which paves the way for further maintenance by comparing with previous image data. Furthermore, other non-destructive testing (NDT) technologies can be integrated into the current one to achieve more reliable results.

The AI-assisted systems act as a backup system if the human professional or operator misses a critical defect in CH. Still, the AI model guarantees that the defect is captured and detected, thus assisting the engineers. The video feed enables the digitization of the CH stock and presents the locations of defects in an understandable manner to the client. The assessments and processed video feed can be placed in the Heritage Building Information Modelling (HBIM) tools, which can further serve as a permanent digital record of the current damaged condition of historic buildings. It can thus aid in the decision-making process to implement maintenance activities for CH buildings. Thus, post-inspection repair and maintenance procedures, such as sealing of cracks, protective coating, cleaning of façades, and so on, can be carried out. In addition to DL approach for the CH structure, several NDT tools, such as laser scanning, thermal scanning, ground penetrating radar, or sonic tests, can be integrated with the current approach to further gain confidence in the intervention solutions. AI-assisted inspections in the future will become more advanced when high-resolution images are captured, enabling more prevalent use of drones and advanced CV techniques, which will help save inspection time and decrease human errors when compared with traditional naked eye inspections. AI-assisted technologies will provide real-time feed systems that will detect defects on the go and help engineers harness the full power of AI-object detection algorithms. Based on the applications highlighted in this review, it can be inferred that considerable potential exists in the field of AI-assisted visual inspections.

Ethical approval

Presented results do not contain studies with human or animal subjects.

Informed consent

For this type of study, formal consent is not required.

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CRediT authorship contribution statement

Mayank Mishra: Conceptualization, Investigation, Writing – original draft. **Paulo B. Lourenço:** Writing – review & editing.

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