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RESEARCH ARTICLE

The use of artificial intelligence in damage assessment of historical buildings

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Abstract Historical buildings are indispensable for maintaining cultural continuity. Proper restoration is the only way to preserve their original character. At this stage, early and accurate diagnosis of the damage to the historical building plays a vital role in the restoration process. Traditional damage assessment methods sometimes cause erroneous diagnoses and damage to the building. For this reason, non-destructive methods should be developed by utilizing the opportunities provided by technology.

The research aims to develop an artificial intelligence-based damage detection model that can quickly and accurately detect deterioration in historical buildings. The study's scope consists of traditional Gaziantep houses in the city's historical center. The primary materials are high-resolution digital façade images, survey reports of these houses, and the findings obtained in the field research.

The research reveals that deterioration maps, which are prepared with traditional methods by spending intensive labor and time, can be produced with an artificial intelligence-based system. Experts first documented the damages seen on the façades of historic stone buildings, and the model trained with these data was used as a supportive method to determine the types of deterioration. Integrating the system with expert opinions, field studies, and visual documents makes creating deterioration maps more efficient.

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1. Introduction

The concept of cultural heritage is defined by ICOMOS as *"all tangible and intangible assets that have survived from the past to the present, described as a reflection of people's values, beliefs, knowledge and traditions that are in a state of constant change without the bond of ownership"* (ICOMOS, 2013). Architectural heritage buildings represent a significant component of tangible cultural heritage. These buildings serve as a conduit between the past and future generations, thereby assuming the significant role of documenting the architectural identity, living culture, construction techniques, and technology of their respective eras. These buildings, distinguished by their unique characteristics, are subject to various forms of deterioration due to internal and external factors. Internal factors include the building's location and the quality of its construction. External factors include exposure to moisture, war, user error, air pollution, fire, vandalism, and the impact of public works projects (Ahunbay, 2009). This situation damages the structure and causes negative effects such as discoloration, abrasion, efflorescence, spalling, cracks, surface loss, and fungal growth, and in some cases, it causes the destruction of the building by destroying its originality and structural integrity (Mitra et al., 2013). Conservation and restoration works are the basic conditions for historical buildings to continue their existence and ensure their sustainability by preserving their original qualities. These works aim to preserve the authenticity and integrity of the historical building while repairing the structure correctly with minimal intervention. As stated in article 4 of the Venice Charter, the fundamental attitude in the conservation of monuments is to ensure the permanence and continuity of conservation (ICOMOS, 1964). The sustainable conservation approach is a methodical process comprising three sequential steps: anamnesis, diagnosis, and treatment. Anamnesis encompasses identifying the building's characteristics, including its geographical location, the date of its construction, and any restoration efforts undertaken. Diagnosis involves the analysis of the building's material properties, the progression of its deterioration, the types of damage it exhibits, and its overall condition. Treatment involves implementing long-term maintenance strategies, conservation measures, and building applications (Fitzner, 2004). This information contributes to the assessment of the past, present, and future of the building.

In the domain of conservation and restoration, damage assessment studies assume a pivotal role in decision-making processes concerning intervention strategies. Damage assessment studies using traditional methods require intensive time, labor, and resources. In some cases, adverse weather conditions and natural disasters, among other factors, prolong this process, leading to continued deterioration and further damage to the building. Moreover, when these assessments are conducted by individuals lacking expertise in their field, they frequently result in erroneous conclusions and lead to irreversible structural damage. Consequently, the most fundamental approach to safeguarding historical buildings while preserving their integrity is the on-site and precise diagnosis of damages without compromising the building. In such instances, non-destructive testing methods assume paramount importance.

Non-destructive testing methods are techniques that facilitate the detection of damage on surfaces and internal components by examining materials without altering their original properties or causing damage (Dwivedi et al., 2018). Developed using the capabilities offered by technology, these methods, enable faster intervention by revealing damage that cannot be detected using traditional techniques. They are widely used in many fields, such as aviation, energy production, industry, automotive, petrochemicals, and engineering (Kubba, 2008). Today, these methods can be grouped according to how they are applied to structures: visual inspection, electromagnetic testing, moisture measurement methods, thermal imaging, acoustic, and ultrasonic testing, and radiographic inspection techniques (Evans, 2015). Furthermore, technology-based methods, including photogrammetry, digital image processing, and laser scanning, can be employed during the documentation phase of historic building projects. These methods facilitate the analysis and evaluation processes, allowing for more efficient completion within a reduced timeframe.

The non-destructive analysis of historical buildings starts with the visual analysis of the material and structural system (Tavukçuoğlu, 2009). To this end, deterioration maps of the structures are initially prepared by conventional methods. The mapping method has been developed as a modern scientific method for identifying, interpreting, and rating the types of deterioration in the structure for damage diagnosis (Fitzner, 2016). The damage type, distribution, and intensity are mapped and documented using this method in the survey. The selection of an appropriate mapping technique is a critical factor in ensuring the integrity of the edifice during the restoration process. Notably, this process can be time-consuming, and there are instances where it might not yield the desired outcome.

While the above-mentioned non-destructive testing techniques are currently employed in the damage assessment process, the limitations and technological advancements underscore the necessity for developing novel methodologies in the conservation-repair process. In this case, it is imperative to use artificial intelligence technology, essential in our age, as a non-destructive testing method in conservation, repair, and restoration work.

Although there are many academic studies on this subject today, artificial intelligence is not yet used as a non-destructive method in the conservation-repair and restoration process. Among these studies, Mansuri and Patel (2022) developed an artificial intelligence-based automatic visual inspection system using Fast R—CNN. Wang et al. (2019) proposed an automatic damage detection method for two categories of damage (efflorescence and spalling) based on deep learning for historic brick masonry structures. Mishra et al. (2024) developed an automated visual inspection system using the YOLOv5 DL model to accelerate the conservation and maintenance processes and ensure the sustainability of cultural heritage buildings. The dataset contains four types of surface defects: spalling, exposed brick, discoloration, and cracks. These studies show that artificial intelligence technology can be used to determine the correct intervention method by enabling more accurate and faster evaluation of the causes of deterioration in historical buildings. However, a system that can map deterioration by showing all damages on the building surface has not yet been developed.

This study focuses on developing a system for detecting deterioration types and creating deterioration maps of historic buildings, especially those built of stone material, through artificial intelligence. The accuracy of artificial intelligence-based analysis is related to the physical and mechanical properties of the building material. For this reason, the developed method was trained and tested using the MASK-R CNN deep learning algorithm on unique data of stone buildings. However, it should be noted that the system alone is insufficient without human-generated data such as on-site inspections, archival documents, and expert opinions. Therefore, the proposed system is not designed to replace traditional methods but to complement and accelerate them.

2. Conceptual background artificial intelligence deep learning and image recognition

The developments in technology brought about by the Industry 4.0 revolution, the products manufactured, and the technological systems designed, along with the digital advancements in many fields, have become central to daily life, enhancing the quality of social and commercial life while making access to information more efficient and faster. In the design of these systems, automation is used to reduce human labor, intelligent systems are used to draw inferences from data, and intelligent computing terms are used as criteria to perform operations such as monitoring, analyzing, and reporting (Sarker, 2022). Among these technological innovations, artificial intelligence technology is one of the modern technologies widely used across various disciplines today.

Artificial intelligence technology as a discipline was introduced in 1956 by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon at the Dartmouth artificial intelligence summer research project (McCarthy et al., 2006). However, there have been many previous studies on artificial intelligence. McCulloch and Pitts (1943) worked on artificial neural networks in their article, and Turing (1950) work, which started with the question "Can machines think?" was an important step for artificial intelligence technology. McCarthy (2007) defines intelligence as "*the computational part of the ability to achieve goals in the world*" and defines artificial intelligence as "*the science and engineering of making intelligent machines, especially intelligent computer programs.*"

Intelligence, in its broadest sense, is defined as a cognitive ability involving a range of competencies, including the capacity for planning, reasoning, understanding complex concepts, rapidly acquiring knowledge from experience, and effective problem-solving (Gottfredson, 1997). It is the mental characteristics of humans, such as understanding, experiencing, inferring, thinking, and making decisions. Artificial intelligence is an attempt to discover and define the ability of machines to mimic some aspects of human intelligence. In other words, it is the ability to perform tasks required by human intelligence (Jackson, 1985). In other words, it is a computational model that allows computer systems to solve complex problems by learning from data and approximate solutions (Elbeltagi et al., 2022). The advanced problem-solving capabilities of such systems are predicated on analytical models that generate predictions, rules, answers, recommendations, or similar results (Janiesch et al., 2021).

The advent of artificial intelligence technology has enabled the development of systems capable of identifying objects in images and videos. This method, termed object recognition, is a computer vision technique that facilitates the identification of objects present within images or videos (Wang et al., 2022). Computer vision algorithms are based on Deep Learning techniques. Deep learning uses Neural Networks, a multi-layered architecture that mimics the behavior of the human brain (Akinbo and Daramola, 2021). Deep learning algorithms pass data through multiple layers, with each layer progressively extracting features and passing them on to the next layer. The first layers extract low-level features, while later layers combine these features to form a representation (Mathew et al., 2021). Today, the improvement of computer hardware performance and the creation of large-scale image datasets have achieved significant success in computer vision applications such as image classification, object detection, and image segmentation (Ren and Wang, 2022).

The object detection approach constitutes a significant instrument in implementing artificial intelligence-based modeling in historical buildings' conservation and repair process. This approach employs artificial intelligence to predict specific types of damage that occur in the structure, which are introduced to the system quickly and reliably over the image.

3. Research methodology

The artificial intelligence-based damage detection system generates a deterioration map by accurately identifying the types of deterioration observed on the surface of historic stone buildings through the analysis of digital images. The development of the system is based on an object detection model with deep learning techniques. The datasets and artificial intelligence models used in the study are based only on the visual and structural characteristics of historic buildings with stone materials. Wood, adobe, or mixed materials such as stone and mudbrick are excluded from the scope of this study as they have different behaviors and damage patterns. The system's design includes seven distinct stages, as shown in Fig. 1.

The study starts with the data collection process. In this context, the historical city center of Gaziantep, located in the southeast of Turkey, was chosen as the study area. At this stage, fieldwork was carried out; buildings were examined, photographed, and documented on-site. Image data were obtained through high-resolution digital images to document the deterioration observed on traditional Gaziantep houses' facades. The types of deterioration detected on the facades were classified in

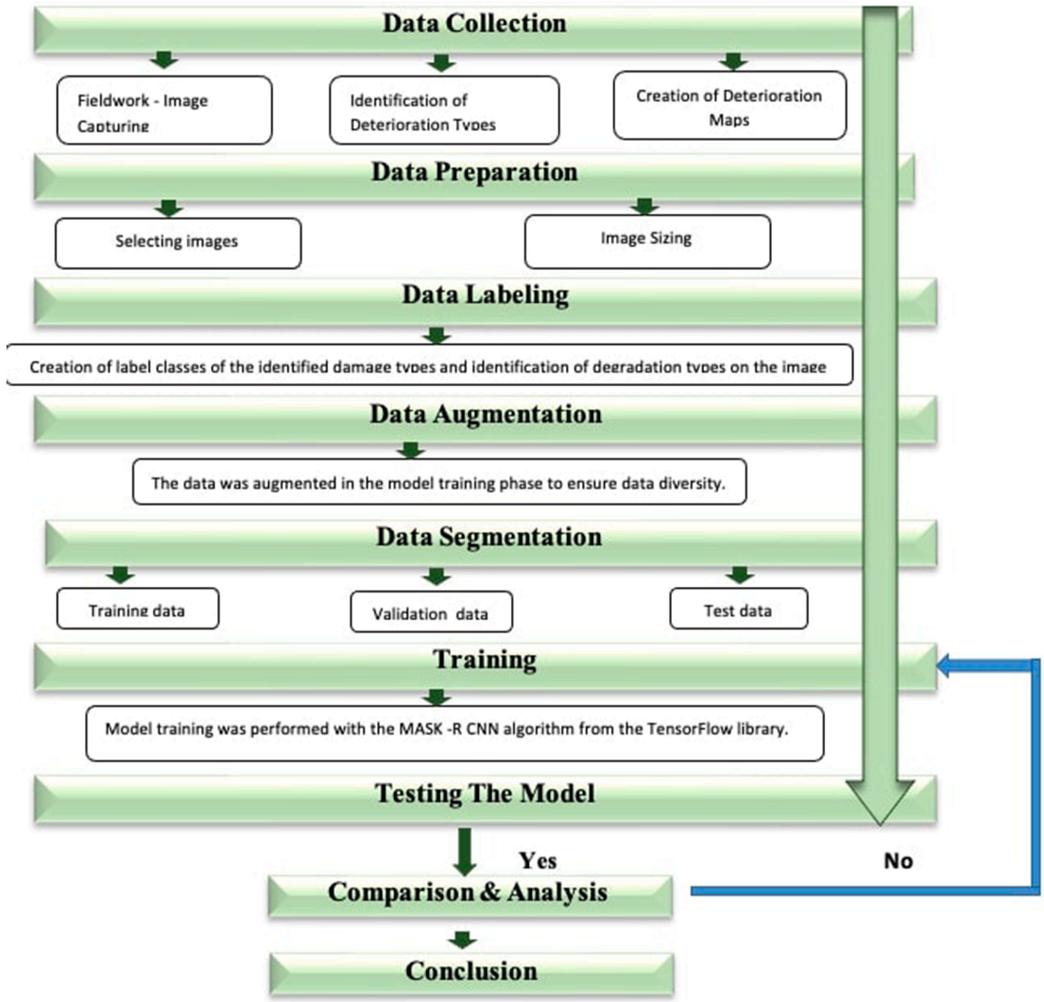


Fig. 1 Research methodology.

line with expert opinions; surveys were made, and deterioration maps were created using traditional methods. In the second stage of study, the images obtained during the field research were selected and resized. In the third stage, an image-based dataset was created by labeling the images of the classified deterioration types to train the model. In addition, textual documents such as survey reports, restoration projects, expert observation notes, and videos were not used directly in the model training. Still, they were used as reference materials for correctly classifying and labeling deterioration types. All data were

Fig. 2 Study area.

Table 1 Types of deterioration in traditional Gaziantep houses.

Material losses	Separations	Material accumulations	Lack of building maintenance/ unconscious intervention in the building
Spillage Swelling Rupture	Capillary Fracture	Paint/Plaster Crust formation Contamination Color change Salinization Mossification	Incorporated annexes Incorrect material usage

Fig. 3 Image samples to be used for training the model.

organized and systematically archived according to date, location, and deterioration type, and only visual data were prepared to be used in the training of the artificial intelligence model. In the fourth stage, images were augmented with data augmentation methods to provide data diversity for model training. The fifth stage, divided the dataset into training, validation, and testing. In the sixth stage, model training was performed using the MASK-R CNN algorithm. Finally, the developed model was compared with the deterioration maps created by traditional methods, and an artificial intelligence-based damage detection system was obtained.

4. Artificial intelligence-based damage detection system

The first step in designing an artificial intelligence-based damage detection system is determining the region selected as the study area. The primary criterion for selecting the study area is the presence of a highly deteriorated street façade. In this case, Tişlaki Neighbourhood Çukurbaşı Street in Gaziantep city centre was selected as the sample area. The sample houses were selected for model testing based on identifying plots 677 and 683 on Çukurbaşı Street. The data required for the development of the model were obtained from traditional Gaziantep houses in the city center of Gaziantep (Fig. 2).

Gaziantep is one of the oldest settlements in Anatolia. Located on the historical Silk Road, the city has enabled different civilizations to live throughout history and has continued its existence as an essential cultural and trade center. The city has many architectural heritage buildings bearing the traces of these civilizations. Traditional Gaziantep houses constitute an integral part of civil architecture buildings. These houses around Gaziantep Castle are essential factors in forming the traditional urban fabric.

The traditional Gaziantep houses were constructed with two or three stories using masonry. The primary building material utilized in these buildings is a stone known as "havara" and "keymıh," which are specific to the Gaziantep region (Yazgan et al., 2005). The durability of stone as a construction material has contributed to the survival of these buildings until the present day. However, numerous factors have contributed to the degradation of these buildings over time, compromising their integrity and causing them to lose their original character. These factors include air pollution, climatic conditions, inadequate maintenance, and unwarranted interventions. Air pollution has been observed to cause crusting, contamination, blistering, and shedding of the material. Furthermore, climatic conditions have been observed to lead to the material's cracking, rupture, and salinization. Following the departure of the original owners, some structures were left empty, while new users occupied others. The unoccupied structures were often neglected, or individuals utilized them for malevolent purposes, such as theft, further compromising the integrity of the structures. Furthermore, various factors, including user interventions and unconscious additions to the structures using materials such as briquettes, paint applications, and billboards, have contributed to the degradation of the building's originality and architectural character, ultimately leading to the deterioration of the traditional street texture. The types of deterioration observed in these structures constitute a significant data source for developing an AI-based damage detection system. Especially considering historical stone buildings' complex and heterogeneous structural characteristics, creating an accurate and comprehensive dataset allows artificial intelligence to produce more precise and reliable results in damage detection.

4.1. Creating the data set

Data is the most fundamental component in machine learning because the model's ability to learn meaningfully and produce accurate results depends on it (Seeniselvi and Nirmala, 2019). A dataset is a collection of relevant data,

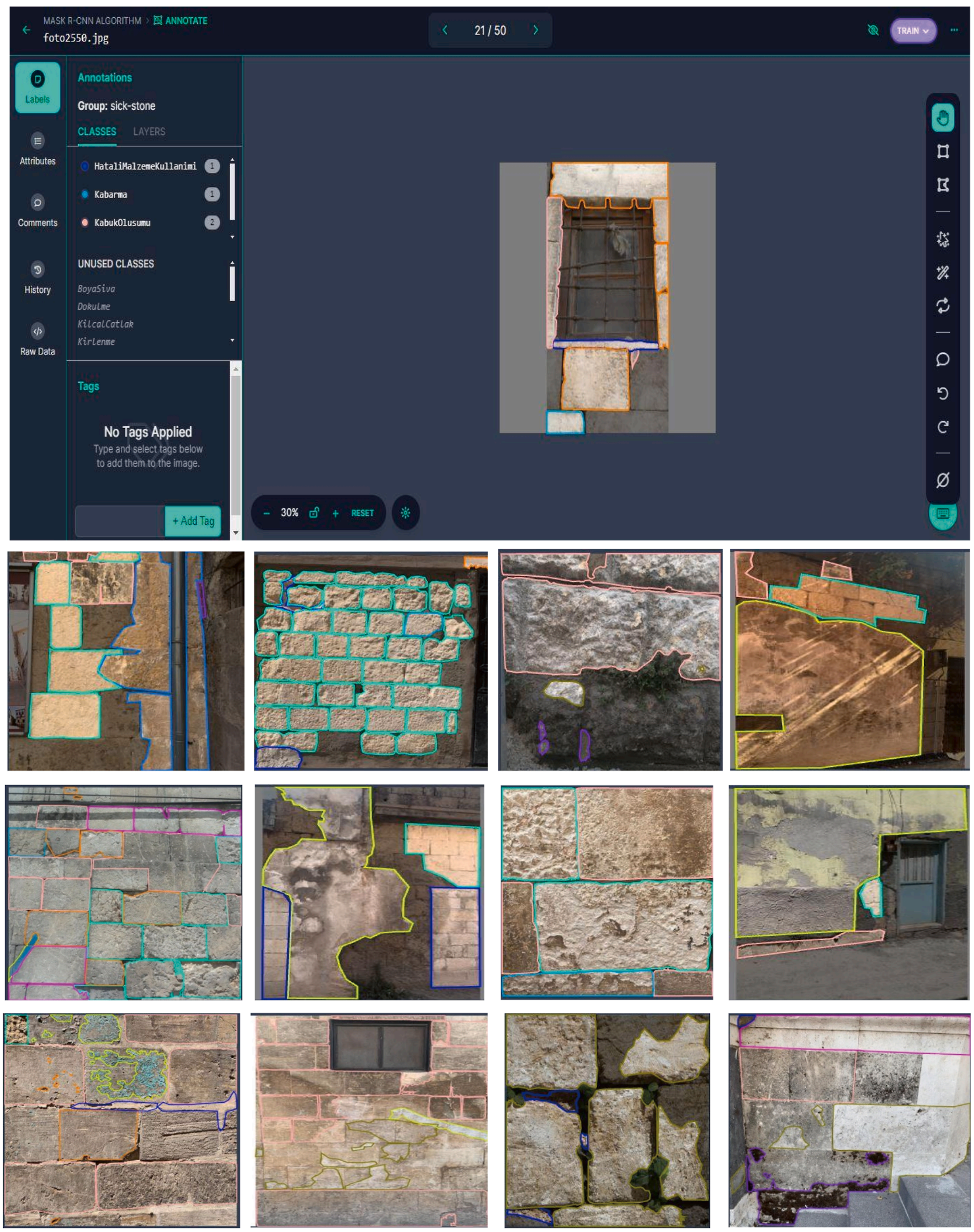


Fig. 4 Image labeling examples.

Table 2 Number of labeling of types of deterioration seen on facades.

Label class	Number of labeling
Paint−plaster	1519
Spillage	1544
Incorrect use of materials	864
Blistering	335
Crust formation	3243
Capillary fracture	55
Contamination	781
Rupture	911
Subsequent additions	471
Color change	784
Salinization	1812
Mossification	731
Total	13050

such as text, images, and videos, prepared in a specific format, and brought together. These are organized by the requirements of an algorithm (Kaur and Singh, 2022).

Within the scope of the system design, it is aimed to learn the model by using the data of the region selected as the sample area and thus to predict the desired results. In this direction, the inputs to be used are passed through certain stages to create a suitable data set. The preparation process includes collecting digital images of the relevant region and the labeling necessary for model training. In the training phase, the model learns various damage from these images and gains the ability to make accurate predictions by making inferences.

4.1.1. Data collection

The model design process starts with data collection. This is the first step in the preparation process and involves deciding on the correct data set depending on the expected output of the machine model to be trained. Here the data source, is identified, the collection method is defined, and the acquired information is converted into digital format for computation (Njeri, 2022).

The data collection process was carried out in two stages. In the first stage, a comprehensive field study was conducted to determine the current condition of the buildings in the study area and to create deterioration maps using the traditional method. In this process, old photographs, maps, registration slips, survey projects, and reports were utilized to investigate the type, function, material properties, and current use of the buildings, as data on the climate, temperature, and rainfall of the region were collected, and deterioration maps were created. In the second stage, the types of deterioration seen on the street facades were determined by visual analysis of the data for model training for system design. Deterioration types were grouped under four main headings: material loss, detachment, accumulation, and misuse repair. Each group was divided into subheadings, and 12 different deterioration types were identified (Table 1).

As mentioned, the image data used in the study belongs to the facades traditional houses in the historical city center of Gaziantep, and a total of 2591 images were obtained at this stage. Some imagery consists of DSLR photos taken with the Sony A7S2 4K (12.2 MP, Full Frame Exmor CMOS sensor, Carl ZEISS 24—70 mm F4/22, 67 mm) camera between September and November 2022. In addition, data was collected with a smartphone camera with 12 MP resolution between 2019 and 2022. For the system to learn the degradation types correctly during the training process, the images were taken from different distances, at various time intervals, and from different angles in other seasons during the time intervals when the degradation types are intensively seen during the year (Fig. 3).

4.1.2. Data preparation

In system design, data is organized according to the working principle of the algorithms. Each algorithm has its own characteristics, and operating principles. Some machine learning algorithms also require the data to meet specific requirements. For this reason, the raw data undergoes a pre-processing process before being fed directly into the machine learning model. Transforming the raw data into a form more suitable for the model can also be described by other names, such as data preparation, data organization, or data preprocessing (Brownlee, 2020).

The data preparation phase requires editing the image. Images usually have different sizes and different features. Each sample must have the same number of features to classify an image in the convolutional neural network for training the model. The model represents the input data as a three-dimensional tensor and contains the pixel values in each channel. The feature tensor must be the same size for all images (Hashemi, 2019).

All the images obtained in this process were collected in a folder, and those with low quality and resolution were removed. Then, the images were resized to 1024 $\times$ 1024 pixels in Photoshop according to the requirements of the convolutional neural network algorithm. Thus, the input data were ensured to be the same

Fig. 5 Dataset segmentation.

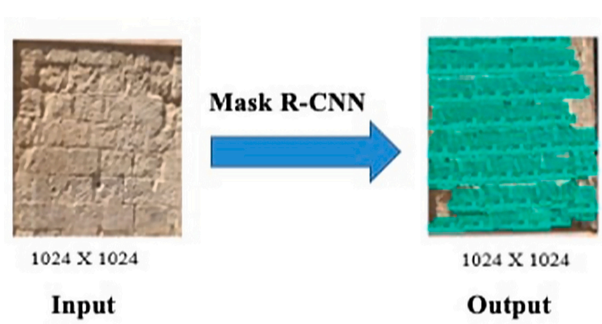


Fig. 6 Image segmentation of the model (He et al., 2020).

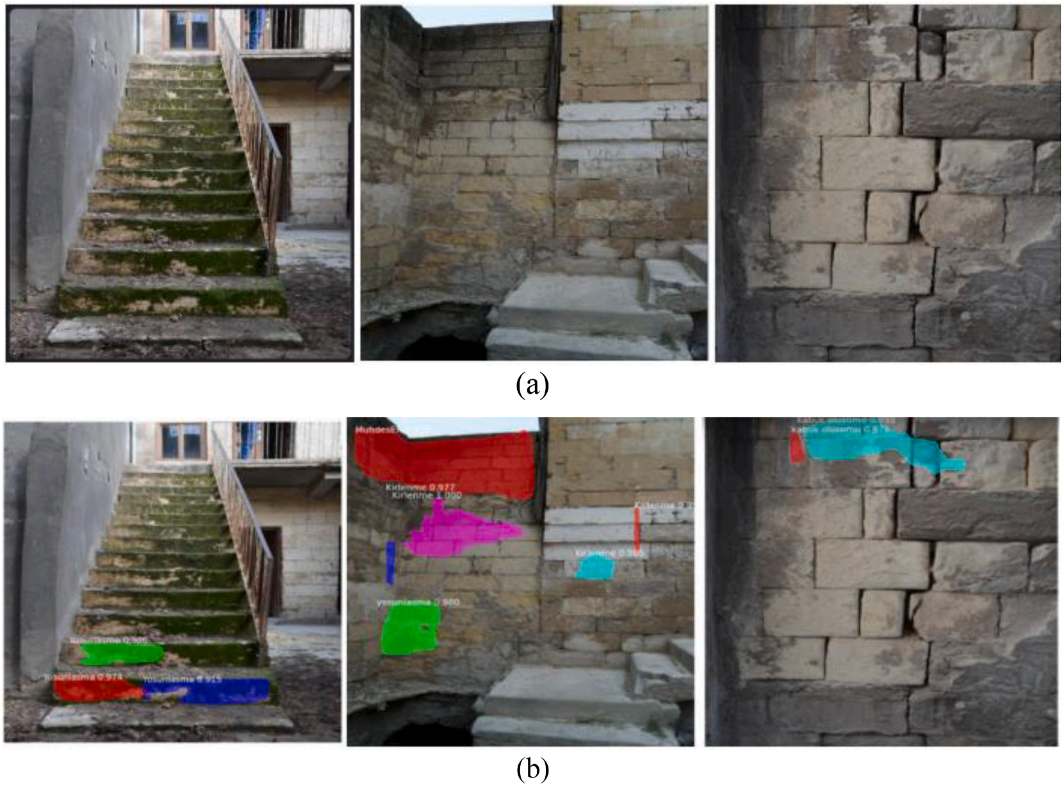


Fig. 7 (a) The test set used in training the model, (b) the outputs of the test set.

size, and the preparation for the image labeling process was completed.

4.1.3. Data labeling

The use of a CNN for image recognition is predicated on its training on a substantial dataset of labeled images containing objects of interest (Krichen, 2023). The fundamental principle of image labeling entails the creation of a mapping that aligns the visual features of an image with meaningful and spatial labels (Sager et al., 2021). In this phase, a bounding box is employed to define the boundaries and position of an object. The configuration of these bounding boxes is subject to variation, contingent upon the geometric characteristics of the objects in question. The types of bounding boxes include semantic segmentation, polygon segmentation, line, and splines. The classification of images is achieved through the application of polygon segmentation in instances where the object's geometry deviates from a rectangular form, semantic segmentation in pixel-based classifications, and the utilization of line and splines in the context of strip detection (Kaur and Singh, 2022).

All image data intended for training were labeled with a web drawing tool in the system's data labeling process. In the first stage, class labels were opened to express various types of distortion. Different colors were then selected for each image label. Given the lack of a defined shape for bounding box distortions, the coordinates were determined using the polygon labeling tool to label the distortions within the images (Fig. 4).

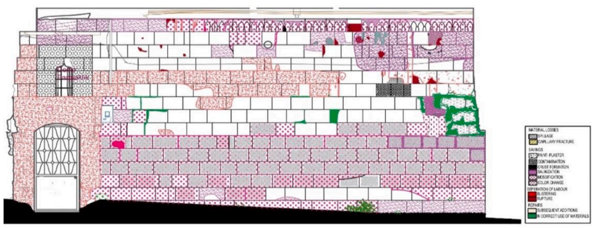
A total of 13,050 labels have been identified in the images. After the completion of this labeling process, the causes of the deterioration types observed in traditional Gaziantep houses can be estimated. This estimation is based on the labeling class and the number of deterioration types (Table 2).

In order to obtain the desired outputs from the model, it is important to label the training data correctly. For this reason, inaccurate labeling and inconsistency between the data negatively affect the training process and reduce the validation rate, which leads the model to make incorrect predictions. After the labeling process, the output of the labeled data is taken according to the algorithm to be used in model training. The data set created for model training was prepared using MS COCO format, which is suitable for the algorithm.

4.1.4. Data augmentation

Data augmentation is defined as the process of transforming existing examples into new examples using label-preserving transformations (Fawzi et al., 2016). This approach enhances the generalizability of models by increasing the limited training data in modern machine learning methods, such as deep neural networks. It is regarded as an effective solution (Lee et al., 2021). The concept of generalizability, as defined in the field of machine learning, pertains to the difference in performance metrics when evaluating a model on previously encountered training data versus test data that is novel to the model (Shorten and Khoshgoftaar, 2019). At this stage, the diversity and accuracy of the data

(a)



(b)

(c)

Fig. 8 (a) 677 Block 46. Parcel street frontage image, (b) deterioration map, (c) artificial intelligence-supported deterioration map estimation.

set are critical factors affecting the performance difference.

In the system design, data augmentation was implemented to enhance the model's performance by enabling it to access a more extensive array of data during training. In this regard, 2591 images were captured during the field studies, which were increased to 15,546 images through rotation and grayscale conversion. Specifically, the images were rotated 90° to the right and 90° to the left and then augmented threefold to enhance the model's performance. This approach yielded more samples during the model training, enabling more accurate predictions.

4.1.5. Data segmentation

Data segmentation is essential in achieving the model's performance and learning capabilities. At this stage, the model's data set is divided into three sets: the training set, the validation set, and the test set. The training set, which comprises a curated collection of images accompanied by labels such as classes, bounding boxes, and masks, serves as the primary repository for the training of a CNN model (Taye, 2023). The validation set is employed to refine the model's performance, including selecting model hyperparameters or regularization parameters (Joseph and Vakayil, 2022). The model's performance, selected and fine-tuned with the training and validation sets, is evaluated using the test set (Yamashita et al., 2018).

The dataset was segmented into three distinct subsets for the training of the model: training, validation, and test sets. Specifically, the training set was divided into 80% of the total data, the validation set into 15%, and the test set into 5%. In this particular instance, 12,437 images were utilized for the training data set, 777 for the test set, and 2332 for the validation data set, all of which were labeled using the designated labeling software (Fig. 5).

4.1.6. Training of the model

The first step in the training process of the system is to select the appropriate deep learning model for damage detection. At this stage, image-based convolutional neural networks (CNN) were selected. The data set created for model training was prepared using MS COCO format, which is suitable for the algorithm. The system's training and testing process was developed using the Mask R—CNN algorithm using the TensorFlow Library at this stage. The Mask R—CNN algorithm efficiently detects objects in an image while generating high-quality segmentation masks for each sample (He et al., 2020). TensorFlow library is one of the deep learning libraries (Géron, 2019). It is an open-source programming language specially designed by Google to program the deep learning model (Charniak, 2018). It includes various functionalities that allow the implementation and exploration of Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) architectures for image and text processing (Bonnin, 2016).

Fig. 9 677 Block 46. Parcel street frontage image and artificial intelligence-supported deterioration map estimation.

The model's learning and prediction capabilities are derived from the labeling of image data. The training process incorporated the Mask R—CNN algorithm, with 80% of the total dataset allocated for training. The image dataset employed consists of 19,556 images, with a total of 98,777 labels assigned to these images. During the training process, the model's slope was updated using a batch size of 32 at each iteration for a total of 50 epochs (Fig. 6).

Following the training phase, the model demonstrated high prediction performance, characterized by a mean average precision (mAP), precision and recall. These high success rates demonstrate the efficacy of the model in damage detection.

4.1.7. Analysis of the model

A small amount of training data was used in the first stage to test the model's applicability for the developed artificial intelligence-based damage detection system. To this end, a set of 65 training data comprising 1024 $\times$ 1024 pixels was meticulously prepared and subsequently trained using the Mask R—CNN algorithm. The outcomes of this training process demonstrate that the inadequacy of the labeled training data and the inaccuracy of the parameter settings negatively impact the model's capacity to make predictions. Consequently, the model exhibits suboptimal performance, resulting in errors and incompleteness in prediction (Fig. 7).

In Fig. 7, (a) represents the test set used in the training process of the model, and (b) represents the outputs of the test set. When the test outputs are analyzed, it is observed that the model incorrectly and incompletely predicts the deterioration of the material. This is due to insufficient training data, which also causes the model to make incorrect predictions. Still, the ability of the model trained with inadequate training data to make predictions is a promising result for the initial stage. In order to improve the performance of the model at this stage, the result is planned to be improved by further developing and diversifying the training data set and adjusting the parameter settings of the model (Figs. 8 and 9).

In Fig. 8, when the deterioration map generated by artificial intelligence is compared with the map obtained by traditional methods, it is observed that with the increase in the number and variety of data, the artificial intelligence model can detect the deterioration on the façade surface in a short time and produce a map. However, the quality and distance of photography directly affected the model's map generation performance. Figure 9 shows that the model could detect all damage types more successfully in images obtained at close range.

5. Conclusion

Historical buildings represent the most significant tangible assets of our cultural heritage. In our country, which is rich in historical and cultural assets, preserving these buildings with their original character and ensuring their transfer between generations stands out as an essential goal. The main objective is to provide urban identity, social memory, and cultural continuity. Undoubtedly, it should not be forgotten that our country is a party to international agreements on protecting architectural heritage. In this framework, preserving, maintaining, and repairing historical buildings in line with their original character is essential. However, before the repair process, correctly analyzing the causes of deterioration is critical in making correct and effective intervention decisions. Correct restoration interventions are only possible with an accurate and comprehensive damage assessment. Restoration practices are not simple procedures to be rushed or carried out with superficial information. Damage assessments carried out with traditional methods are sometimes inadequate and can lead to incorrect assessments, causing buildings to lose their original character. However, today's technological developments necessitate adopting more innovative and scientific approaches to conservation processes.

In this direction the findings obtained as a result of this research, which aims to develop an artificial intelligence-based method for faster and more accurate detection of deterioration types seen in architectural heritage buildings, have shown that technology can be used effectively in cultural heritage protection and sustainability. Using Mask R—CNN, an existing deep learning method, a model trained with the specified data was created, and this model was able to predict the damages in the structure over the images. The model was tested on the images obtained from the sample areas and it was seen that it detected the damage to the facade surface of the historic stone building and created deterioration maps in a short time. Despite the possibilities the developed model provides, there are limitations in some cases. The model's accuracy is directly related to the high number of classes in the dataset and the structural complexity of these classes. In addition, the shooting distance (proximity, distance), quality, and angle of the images used are among the critical factors affecting the model's performance. For the model to achieve higher accuracy rates, better-quality images should be used, and data diversity should be increased. Another limitation is that although artificial intelligence can detect damages visible on the facade surfaces of historic stone buildings, it cannot detect decompositions such as moisture, cracks, freezing, and thawing in the material's internal structure. This poses a risk for the historic building. Therefore, future studies can solve this problem by integrating artificial intelligence with structural analysis methods such as thermal imaging, ground penetrating radar (GPR), and ultrasonic tests. In addition, although this study was developed on historical stone buildings, it is envisaged that it can be adapted to structures made of wood, adobe, or mixed materials. Thus, artificial intelligence-supported damage detection systems will become an effective analysis tool for stone, and different types of buildings. This will significantly contribute to the development of holistic and sustainable approaches, especially in conserving historical textures. However, artificial intelligence should not be used as a decision-making tool alone in restoration processes; it should be evaluated as an analysis tool that can provide more accurate results by supporting expert opinions, on-site examinations, and survey studies. This study has demonstrated that artificial intelligence technologies can be used as an effective and applicable method in cultural heritage conservation, at the same time, it is expected to guide future academic research in this field.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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