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AI ROLE IN INITIAL STAGE OF STRUCTURAL HEALTH MONITORING IN CIVIL INFRASTRUCTURES

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Abstract

Structural integrity assessment is crucial for ensuring the safety and longevity of infrastructure. Cracks, a common structural defect, can originate from various causes, including mechanical stress, environmental factors, and material degradation. These cracks are classified based on their orientation (horizontal, vertical, diagonal), cause (structural, non-structural), and propagation behavior (surface, subsurface, thorough). Traditional crack detection methods such as Visual Inspection Analysis (VIA), Acoustic Emission (AE), and Ultrasonic Testing (UT) have been widely used for in-situ analysis. These methods, while effective, often involve high costs, time-consuming manual inspections, and limited accuracy in complex structures. Digital Image Processing (DIP) and Visual Inspection (VI) offer cost-effective solutions for initial crack detection, but their effectiveness is limited without automation. Recent advancements in Artificial Intelligence (AI) have revolutionized Structural Health Monitoring (SHM) by automating crack detection and classification. Machine Learning (ML) and Deep Learning (DL), key AI subfields, provide robust solutions for automatic crack identification by analyzing image patterns and structural datasets. ML models use predefined features extracted from images or sensor data, while DL models operate directly on raw images or feature vectors to classify cracks accurately. These AI-driven approaches significantly enhance the efficiency and accuracy of crack detection compared to traditional methods. However, challenges such as data availability, model generalization, and real-time implementation need to be addressed for widespread adoption. The integration of AI with existing SHM frameworks holds great potential for improving structural assessment, reducing maintenance costs, and preventing catastrophic failures.

Keywords: *SHM, traditional tests, DIP, AI, ML, DL*

1. Introduction

Structural Health Monitoring (SHM) is a process used to assess the strength and longevity of structures by analysing sensor data. It plays a crucial role in various fields, including aerospace, civil engineering, and mechanical structures. Traditional methods of inspection often rely on manual assessments and periodic evaluations, which can be time-consuming and may not capture real-time changes. However, by the late 20th century, SHM

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methodologies advanced to include both visual and auditory signal processing techniques [1]. In contrast, SHM systems provide continuous monitoring, enabling engineers to detect potential issues early and make informed decisions regarding maintenance and safety. SHM was conducted through advanced algorithms that process data collected from a network of sensors embedded within the structures. These sensors measure parameters such as strain, temperature, and vibration, allowing for a comprehensive understanding of the structural health over time.

Technological advancements have further enhanced SHM, enabling continuous monitoring, automated damage detection, and predictive maintenance. Modern SHM synchronises through IoT and provides real-time monitoring of buildings, as shown in Figure 1.

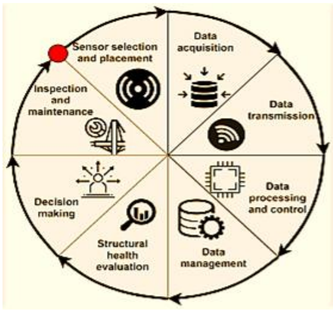

Fig. 1. SHM monitoring [2]

The ultimate goal of SHM is to ensure the safety of both living and non-living elements within structures. This objective has been significantly achieved through modern SHM practices, which leverage sensor data to enable real-time monitoring and proactive maintenance, as illustrated in Figure 1. Modern SHM practices minimise computational cost in design and maintenance compared to conventional SHM, as shown in Figures 2 & 3.

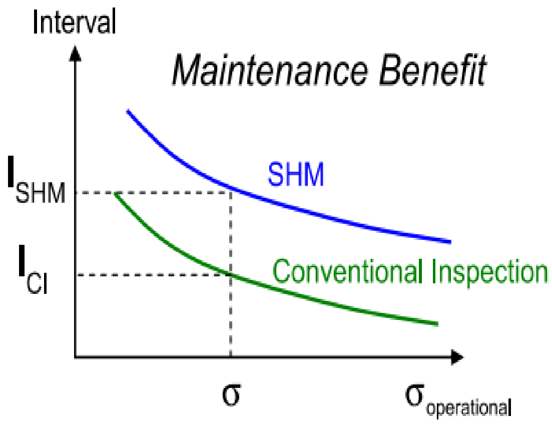

Fig. 2. Maintenance Benefit [1]

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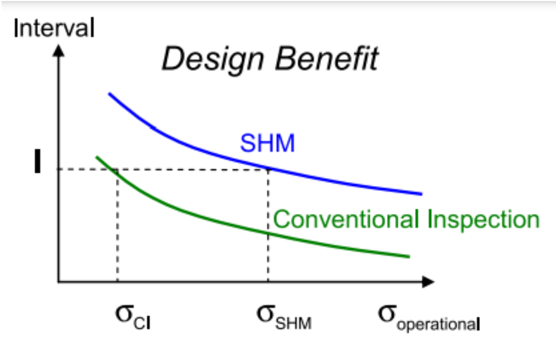

Fig. 3. Design Benefit [1]

The functionality of SHM is to identify the defects at an earlier stage and take preventive measures to avoid the catastrophic failures. Based upon the material and its curing process, the defects may vary for each field. Defects in buildings are critical, as they can cause damage to both living and non-living things. Hence, SHM is highly preferred in various industries, including construction and infrastructure management. By implementing SHM systems, stakeholders can ensure the longevity and safety of structures, ultimately reducing maintenance costs and enhancing overall performance.

Based on that, the study [3] highlighted the defects in the building as follows: cracks, water problems, wall cracks, spalling, and column buckling as shown in figure 4.

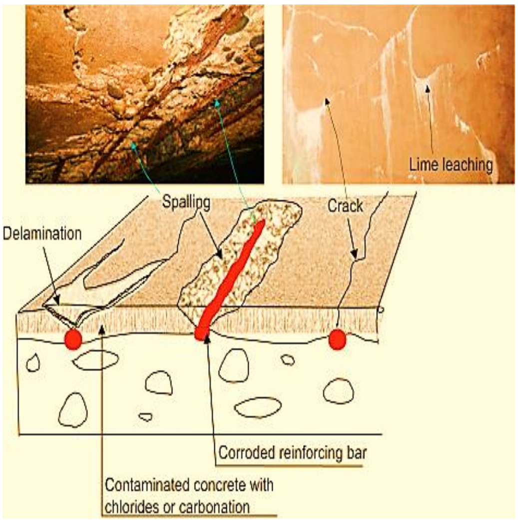

Fig. 4. Defects in building

To observe the defect frequencies, they conducted a study on defects in five houses in Australia. Based on their findings, it was determined that wall cracks were the most prevalent issue, occurring in over 60% of the surveyed houses. Additionally, water problems were identified as a significant concern, often leading to further structural damage if not addressed promptly.

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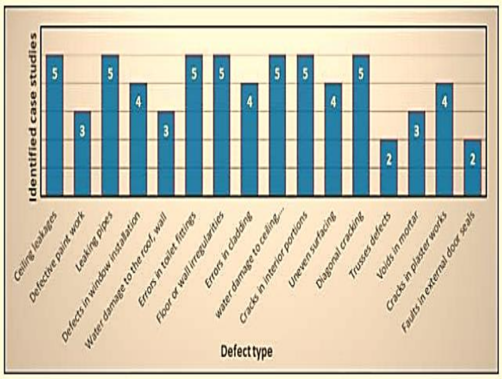

Fig. 5 Defects Frequencies [3]

Figure 5 showed that the cracks and their differences were prominent defects in their case studies. Generally, cracks may occur due to different reasons like environmental factors, chemical reactions, and poor construction. But long-term cracks reduce the building's strength, and they also lead to other damages like corrosion. Not only the time span but its occurring location and its propagation also influence the building damage [4]. This shows that the crack detection is a prominent one in SHM.

Visual Inspection Analysis (VIA) is a widely used method for analyzing crack types based on their width properties. Acoustic Emission (AE) and Ultrasonic Testing (UT) are commonly employed in in-situ experiments, offering unique capabilities for detecting crack propagation due to corrosion, monitoring crack growth in historical structures, and identifying cracks in various materials. Digital Image Processing (DIP) and Visual Inspection (VI) testing provide cost-effective solutions for crack detection and measurement.

The integration of Artificial Intelligence (AI) techniques enhances the first stage of crack detection in Structural Health Monitoring (SHM) by analysing both images and datasets to recognize patterns associated with different crack types. Machine Learning (ML) and Deep Learning (DL), as AI subfields, enable automatic classification, with ML utilizing extracted image or data features for classification, while DL processes raw images or feature vectors directly. Both approaches rely on supervised learning, requiring annotated datasets for accurate crack classification and analysis.

2. Cracks in Structural Health Monitoring

A visible fissure like separation between the structural components of building is called cracks. It may occur due to several factors like foundation settlement, temperature difference, moisture and poor construction techniques. Even with good construction techniques, cracks are unavoidable one [5]. But it can be controlled by taking preventive measures timely.

Generally, cracks are of two types namely active cracks and dormant cracks. Dormant cracks are the cracks which does not propagate through the building over the time. While active cracks are the live cracks which propagates through the building over the time and it requires serious attention to stop its crack propagation throughout the building.

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a. Significance of Cracks

Based on IS 456 2000, the cracks whose width lesser than 0.3 mm requires less attention. But if this crack occurs on the structures, it requires preventive measures as it can moisten the building [5]. Based on its width, cracks are classified as follows:

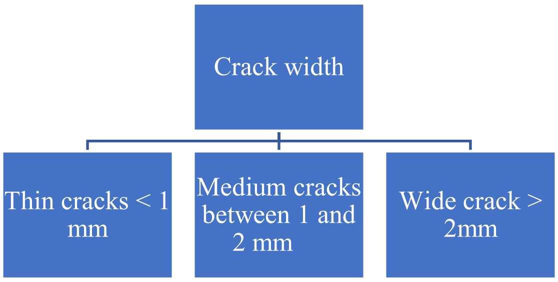

Fig. 6. Width based crack classification [6].

Similarly, based on its location it is classified as structural and non-structural cracks. Structural cracks are the cracks which occur on the building structures like Columns, slab, and beams. These types of cracks require immediate attention to prevent propagation and serious damages to the building. While non-structural cracks are the cracks which occurs on walls, driveway and parapet walls. Even though it does not propagate over time, preventive steps can help to minimize the deterioration.

b. Causes of cracks

In SHM, identifying the cause of defects is the second stage of process. Because identifying the root cause helps to take corresponding preventive measures easily and minimize its damage impact on the buildings. Based on this, the major causes of cracks are as follows:

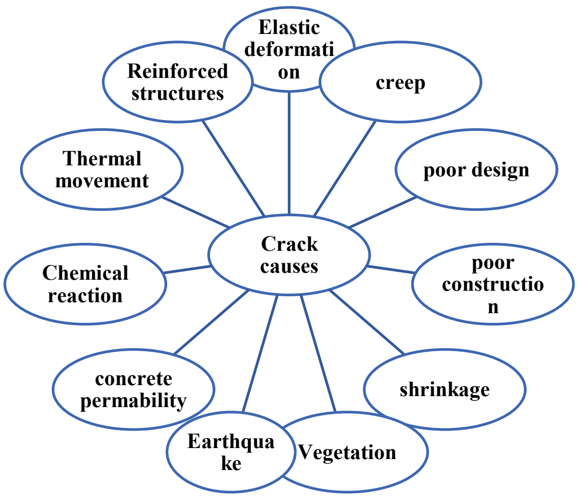

Fig. 7. Crack Causes [7].

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The aforementioned factors were common for all types of crack formation. Any one of these factors alters the small pores in the structure and that leads to a different type of cracks.

i. Causes of concrete cracks

For concrete cracks also, the aforementioned factors are the causes for the formation of cracks. But it varies for each type and is presented in the table 1.

Table 1. Concrete crack causes [8]

Type	Primary Cause	Secondary cause	Location	Formation time period
Plastic settlement	Bleeding	Early drying	Top of columns, deep section, slab	10 min to 3 hours
Plastic shrinkage	Early drying, steel near surfaces	Low-rate bleeding	Roads & slabs	30 min to 6 hours
Early Thermal Contraction	Excess temperature	Rapid cooling	Thick Walls and slabs	One day or two to three weeks
Longterm drying shrinkage	Inefficient joints	Inefficient curing	Thin slabs and walls	Weeks to months
Crazing	Impermeable works	Rich mixes	Slabs	Within a week
Reinforcement corrosion	Excess calcium chloride or cover lacking	Poor quality concrete	Slabs, columns, beams	> 2 years
Alkali reaction	High alkali cement reactive		Damp location	> 5 years

With this information, the buildings can be checked periodically to identify these cracks and its corrective measures can be taken.

ii. Causes of cracks in Steel

Like concrete cracks, cracks can also occur in steel through any one of the crack formation causes.

Steel Type	Type of Defect
Billet	Cracks, scratches
Hot strip	Cracks, longitudinal scratches, transverse scratches, scales, delamination, roll marks, pit defects, seams, inclusions
Cold strip	Bruises, slags, inclusions, seams, oxide scales, cracks, holes, feather roll marks,
	Latex marks
Stainless steel	Slag inclusions, scratches in pickling, scratches
Rod/bar	Cracks, scratches

Fig. 8. Steel Defects [9]

According to the study in [9], the aforementioned defects will be seen in steel and it may occur at any period of curing process. Identifying these defects at an earlier stage can prevent its propagation to the concrete structures.

c. Impact of cracks on structural integrity

The major impact of cracks on the building it alters the building structure and untreated cracks results in pathway for contamination and damping concrete in the structure. Apart from this, the long terms and large number of cracks reduces the resale value of building. According to the study in [10], the impact of cracks in building is presented in pictorial format in figure 9.

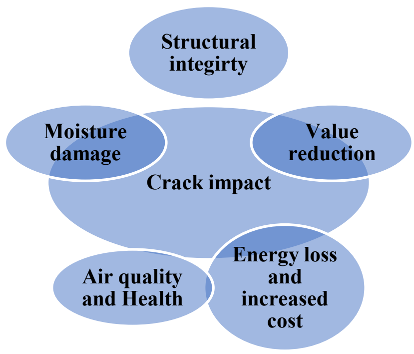

Fig. 9. Impact of Cracks [10]

It can be seen that the factors that causing cracks in steel and concrete remains same but its identification and propagation time period is different. Apart from this, each type of crack has unique feature and that helps to identify the crack types and it root causes.

3. Types of Cracks in SHM

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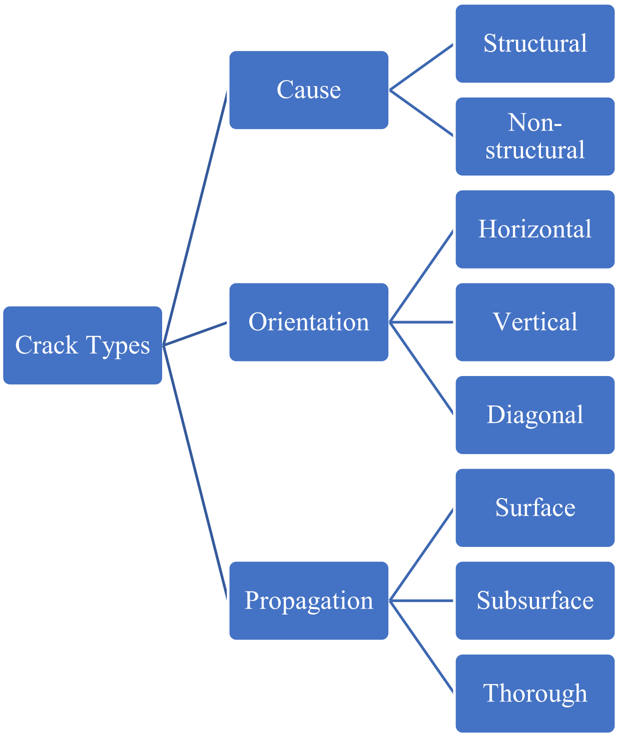

Fig. 10. Crack Classification

a. Classification by Cause

i. Structural Cracks

- Flexural Cracks: These occur in reinforced concrete beams and slabs due to excessive bending. They appear vertically in the tension zone and widen toward the middle. If left unaddressed, they can lead to structural failure.
- Shear Cracks: Typically diagonal, these cracks form near supports due to high shear stress. They indicate insufficient reinforcement or overloading and may lead to sudden failure.

ii. Non-Structural Cracks

- Plastic Shrinkage Cracks: Occur on fresh concrete surfaces due to rapid moisture loss before setting. These cracks are shallow but can deepen over time if not properly cured.
- Drying Shrinkage Cracks: Appear when hardened concrete contracts due to moisture loss. They are fine, widely distributed cracks that can impact durability but not structural strength.

b. Classification by Orientation

- Horizontal Cracks: Often found in retaining walls and foundations due to lateral earth pressure or temperature variations. They can indicate serious structural instability, especially if located near the base of a wall.

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- Vertical Cracks: Common in load-bearing walls, they are caused by settlement or shrinkage. They usually do not affect structural stability unless they widen significantly.
- Diagonal Cracks: These cracks develop due to differential settlement or shear stress in beams and columns. They can be severe and require immediate reinforcement.

c. Classification by Propagation

- Surface Cracks: Found on exposed surfaces, they do not penetrate deeply but can reduce durability by allowing moisture ingress. Common causes include shrinkage and thermal expansion.
- Subsurface Cracks: Hidden within the material, these cracks are difficult to detect without non-destructive testing (NDT). They can lead to spalling and corrosion of reinforcement.
- Through Cracks: These extend across the entire section, compromising structural integrity. Immediate repairs, such as epoxy injection or grouting, are necessary to prevent collapse.

4. Traditional Crack Detection Techniques

In ancient days, the cracks were detected visually during the periodical inspection of the buildings. In later years, the process has been improved by incorporating the technology advancements. This section highlighted those traditional techniques which are used for crack detection.

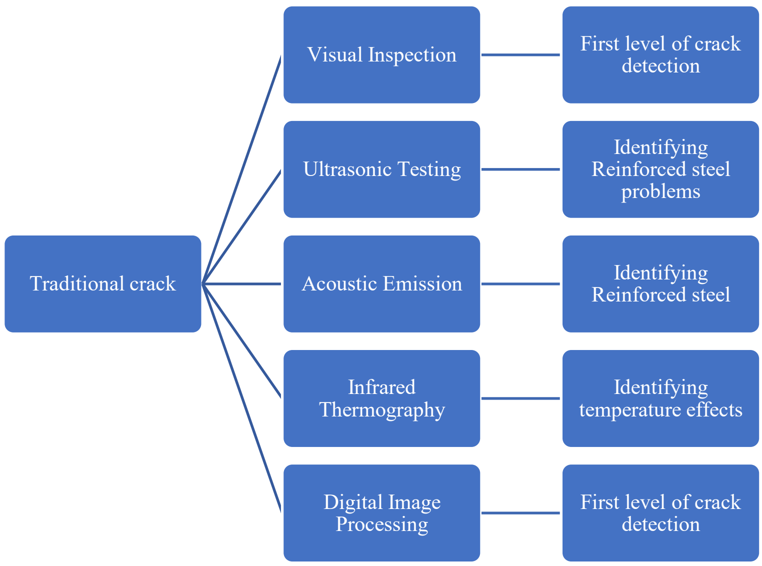

Fig. 11. Traditional Crack detection

a. Visual inspection

In [11], a visual inspection-based crack analysis was performed in the Jindal Institute of Technology institutions. From their inspection, they found out the improper design practices

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are responsible for the thin, medium and sever cracks in the building. They also analysed the root cause of the cracks for taking corresponding preventive measures.

In [12], the visual inspection of cracks was performed in two types of residential areas. Here, they analysed the structural cracks on columns, beams and slabs and categorize them into five classes range from very slightly to very severe using their crack width. From their locality's nature, it was observed that the corrosion and soil settlement were the root cause of the cracks. Another VI based analysis was performed for the residential unit building walls and the crack width was used to classify them crack nature and strength [13].

b. Ultrasonic Testing (UT)

An early-stage detection of corrosion-based attacks in concrete was studied through in-situ experiments in [14]. Here, the concrete bed was designed with different stage of corroded steel in it and observed the concrete properties through Ultrasonic Wave testing. From the wave amplitude, it detects the corrosion at an earlier stage itself.

In [15], different types of Ultrasonic sensor and diagnostic tool for performing SHM in building and bridges were discussed. They also stated that the UT is useful for analysing the corrosion and cable damage in the building. Each sensor and diagnostic tool have unique properties and functionalities for analysing the cracks. Like [14], study [16] also conducted the in-situ experiments for detecting the corrosion attack impact on concrete cracks using UT. Intensity modulation ratio is an important feature for analysing the crack using UT. In [17] also, in-situ experiment is conducted to analyse the corrosion-based cracks on the subsurface of the concrete. Here, UT was combined with thermography testing to enhance the crack detection.

c. Acoustic Emission (AE)

AE test is used to estimate the crack propagation in concrete through in-situ experiments [18]. Here, the tensile and shear cracks were analysed using the compressive and flexural strength analysis using sifted b-analysis. In [19] also, AE test was conducted as in-situ experiments for observing the crack propagation in brick masonry. Here, the temperature effects on cracks also analysed, while [20] reviewed the AE testing role in analysing the crack propagation and stability in the historical building. It also highlighted the b-value testing role in identifying the crack propagation in the building. It requires more than four sensors for analysis. Similarly, [21] & [22] also used AE for analysing the crack propagation in historical buildings.

d. Infrared Thermography

As compared to other tests, Infrared thermography (IRT) testing is a difficult one because this test can be influenced by external factors air and temperature surrounding it. Hence, this test should be done properly for crack identification [23]. In [23], IRT is conducted on a building façade in Lisbon city using sun as its radiating source. Then, IRT image pixel

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properties were used for identifying the cracks. In [24], a deep survey of IRT role in identifying defects in the building was conducted. They also stated that the IRT can be influenced by external factors easily and it requires proper analysis scenario for best results. IRT test is an expensive test procedure for large buildings [25]. It was identified through by performing IRT on different concrete structures like bridge, cooling tower and so on. From that, it was observed that IRT is an expensive one as it requires proper test setup for analysis.

e. Digital Image Processing

In the aforementioned tests, the real time monitoring of data is used for analysing the cracks. While in this test, the real time monitoring or offline test can also be performed because it utilizes the image as input for analysing the cracks. Here, the image undergoes different types of processing like pre-processing, filtering, thresholding, feature extraction & reduction and classification for crack detection. In Digital Image Processing (DIP) test, three types of analysis can be performed as follows: Crack detection, classification and measurement using aforementioned process [26]. In [27], OTSU thresholding and binarized image properties were used for analysing the surface crack detection. In [28], crack detection and measurement is performed as in-situ experiments using image correlation property. In [29], DIP test is combined with UAV for crack detection. Here, UAV is used for capturing the wall images lively and DIP is used for crack detection and measurement. The spatial and frequency domain filters like Prewitt, Sobel, Laplacian and Gaussian filters were used for identifying the cracks and its width. The test results showed that the Spatial filters are best for faster crack detection using UAV images. Like [29], [30] and [31] also combined UAV and DIP for crack detection in bridges and building respectively. In [30], like [29] filters used for crack detection but it also used kmeans clustering is used for classification.

f. Challenges and limitations of conventional methods

- Visual Inspection analysis is used for analysing the basic levels of crack types using their width property.
- AE and UT tests were mostly conducted using in-situ experiments.
- Each test has unique properties as follows:
  - UT is used for analyse the crack propagation through corrosion attacks.
  - AE test is used for analyse the crack propagation in historical buildings.
  - IRT is used for crack identification.
  - DIP is also used for crack identification and classification.
- IRT test is an expensive test

5. Role of AI in Crack Detection and SHM

Among different types of traditional testing, DIP and VI testing were cost effective for crack detection and measurement. As crack detection, measurement and classification are the first stage of crack detection in SHM. This process can be automated using AI techniques. Because AI technique can process both image and dataset for identifying the data pattern for

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each crack type and this pattern can be used for automated crack classification. For an initial stage of processing, the AI technique can be used for automated crack detection and classification. Machine Learning (ML) and Deep learning (DL) are two sub classes of AI for automatic classification. In ML, the image or data features will be used as input for classification. While in DL, the direct input image or feature vectors can be used as input for classification. Both ML and DL are supervised classification that uses annotated images or features for classification.

a. Machine Learning-Based Approaches

In [32], SVM and clustering technique is used to identify the concrete defects like rebar, spalling, cracking and efflorescence. Among this, the SVM achieved 99.3 accuracy in crack detection. In [33] also, SVM classification was used along with morphological operations and binarized image properties for crack detection. It used six properties like mean width, perimeter, Area, Length width, Occupancy rate and compactness for classification. The latter three features achieved higher accuracy using Radial basis based SVM classifier.

In [34], a different type of feature set called seismic feature set from seismic analysis on a three-benchmark model building is used for analysis. Here, around seven types of features were used for crack detection using SVM, K-nearest neighbour (KNN) and Naïve Bayes (NB) classifiers. The classifiers were self-tuned with hyper-parameter optimization and KNN classifier produced the best results in identifying the shear cracks in the walls.

In [35], the images were collected and processed using different types of filters like Gabor filter, edge filters and followed by feature extraction and reduction using SALP optimization algorithm. Here, they utilized fusion approach called SVM and Dempster Shafer fusion algorithm for final crack detection. In [36], the signals from Piezoelectric transducer during in-situ experiments were used for analysis. The Gaussian Mixture model (GMM) is used for feature extraction and it detects cracks through both SVM and self assisted SVM. Among these algorithms, SA-SVM produced the best results. In [37], metallic surface defects was determined using resonant frequency data using three types of classifiers namely, SVM, KNN and Logistic regression (LR). Among these, KNN algorithm determined the metallic surface cracks effectively.

Most of the ML models were used for crack detection and classification, while in [38], a new model called Genetic expression Programming (GeP) was used for finding the crack width in self-healed concrete samples. The GeP model utilizes the insitu parameters for analysis. In [39], the damages caused by the earth quake are analysed using machine learning models on south Napa Dataset. Among different ML models, Random Forest (RF) accurately detects around sixty percent of test set accurately.

In [40], the crack detection in road is performed using different types of ML like SVM, KNN, RF, Bagged tree and hybrid model. Here, the images were processed using heuristic algorithm for crack detection and then processed with binarization for crack feature extraction. Hybrid model with heuristic approach outperforms other classifier performance.

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Like [34], in [41] also seismic features were used for analysing the earthquake damage to the building along with their structural properties. Here, different types of ML like, SVM, RF, KNN, and decision tree were used. SVM and RF only graded the damage accurately than other algorithms.

b. Deep Learning Based approaches

In [42], different types of DL models like Unet, Deep lap V3 and V3 plus are used for identifying the cracks in the brick masonry. DL approach can outperform other models along with using image and other feature vectors. In [43], the UAV images of Sydney location was used for crack analysis using different types of DL like CNN, Cycle GAN and guided filter-based CNN. The guided filter-based CNN outperforms the other models using active feature extraction from the images. In [44], the transfer learning process on Alexnet is proposed for automated crack detection using UAV images.

Instead of images, the seismic signals from lab experiments are used for analysis in [45]. Here, the CNN is used for processing these seismic signal and classification. In [46] and [47], the pre-trained models like VGG-16 and Yolo are used for crack detection in concrete surfaces. In [48] and [49] surveyed the DL role in crack detection in civil infrastructures and transformation based DL achieved better results.

c. Data Acquisition and Processing

Most of the research works collected the dataset manually and annotated with the experts for further processing in ML and In order to enhance the DL performance, the transformation called Wavelet transform was used in [50] for enhancing the input images for analysis and this DL [32], [34]. In some cases, the images were collected using UAV like [33]. In some cases, like [34] and [36] dataset was taken from in-situ experiments. In such scenario, the features from these experiments will be used for crack detection using ML models.

DL model performance is based on the large dataset to avoid over fitting problem. To overcome this, data augmentation will be performed on the dataset to increase the size. Likewise, in [43], data augmentation is performed using rotation and cropping for sixteen times to increase its dataset size. Like ML, DL can also process seismic signal and it can be seen in [45]. Like augmentation,transformation technique also used with DL to improve its detection [50].

6. Comparative Analysis: Traditional vs AI-Based SHM

a. Accuracy and Reliability

Traditional crack detection methods, such as Visual Inspection (VI), Ultrasonic Testing (UT), and Acoustic Emission (AE), have been widely used for structural health monitoring (SHM). However, these methods often rely on manual assessment, leading to subjectivity, human error, and inconsistencies in results (Dutta et al., 2020). AI-driven techniques, particularly Machine Learning (ML) and Deep Learning (DL), offer enhanced accuracy by automatically identifying patterns in crack images and sensor data. DL models, such as

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Convolutional Neural Networks (CNNs), can detect and classify cracks with high precision, reducing the dependency on human expertise (Cha et al., 2017). Moreover, AI models trained on diverse datasets improve reliability by adapting to different crack types, materials, and environmental conditions, ensuring a more consistent and objective evaluation.

b. Efficiency and Automation

The manual nature of traditional inspection methods makes them time-consuming and labor-intensive, requiring skilled personnel and specialized equipment for field assessments (Zhao et al., 2019). AI-based systems, on the other hand, significantly enhance efficiency by automating crack detection and classification using real-time image processing and sensor data analysis. For instance, CNN-based models can analyze thousands of images within seconds, providing instant defect detection with minimal human intervention (Avci et al., 2021). Additionally, AI-driven SHM systems can be integrated with drones and robotic systems for large-scale inspections of bridges, tunnels, and historical structures, further improving automation and reducing inspection time (Rathore et al., 2022).

c. Cost-Effectiveness and Scalability

Traditional crack detection methods often require expensive equipment, extensive labor, and repeated inspections, increasing overall maintenance costs (Li et al., 2018). AI-based approaches significantly reduce costs by minimizing the need for physical inspections and optimizing maintenance schedules based on predictive analytics. The scalability of AI-powered SHM systems allows them to be deployed across various infrastructure types, from small buildings to large bridges, without significant additional costs. Furthermore, cloud-based AI models enable remote monitoring and decision-making, further improving cost-effectiveness (Feng et al., 2021). While initial AI implementation may involve investment in hardware, training datasets, and model development, the long-term benefits outweigh the costs, making AI a viable solution for large-scale infrastructure monitoring.

7. Challenges and Future directions in AI-Based SHM

The integration of Artificial Intelligence (AI) into Structural Health Monitoring (SHM) has significantly improved the detection and prediction of structural anomalies. However, several challenges impede its widespread adoption, including data availability, generalization issues, computational demands, and integration with existing SHM frameworks.

A primary challenge is the scarcity of labelled data necessary for training AI models. Structural failures are infrequent, resulting in limited datasets that often lack the diversity required for robust model training. Manual annotation of SHM data is labour-intensive and costly, necessitating expert involvement. Environmental factors, such as temperature fluctuations and sensor noise, further complicate the labelling process. Techniques like data augmentation, semi-supervised learning, and transfer learning can be employed to mitigate these issues.

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Another significant challenge is the generalization and domain adaptation of AI models. Models trained on specific structures or environmental conditions often struggle when applied to different materials, designs, or sensor configurations. Domain shifts caused by factors such as aging infrastructure and environmental changes can further degrade model performance. To address these challenges, domain adaptation techniques like adversarial training and domain-invariant feature extraction can be utilized. Ensemble learning, continuous learning methods, and hybrid AI-physics models play a crucial role in ensuring predictions align with real-world structural behaviour, increasing reliability and trustworthiness.

Computational costs and real-time implementation present additional hurdles in AI-based SHM. Deep learning models require substantial computational resources, making real-time monitoring challenging. High inference latency can delay damage detection, posing safety risks, especially in critical infrastructure such as bridges and power plants. Energy consumption is also a concern, particularly for wireless sensor networks in remote locations.

Integrating AI into existing SHM frameworks remains a significant challenge due to compatibility issues with traditional physics-based models and statistical methods. Many existing SHM systems rely on legacy infrastructure that may not support AI-driven solutions. A potential solution to these challenges is the development of explainable AI (XAI) techniques that provide transparency in model decision-making. Methods such as SHAP and LIME can enhance trust by offering interpretable insights into AI predictions. Hybrid AI-physics models that integrate machine learning with traditional finite element analysis can ensure that AI-driven insights align with established engineering principles.

In conclusion, while AI has the potential to revolutionize SHM, several challenges must be addressed to ensure its effective implementation.

9. Conclusion

The detection and classification of cracks in structures are essential for ensuring structural stability and longevity. Traditional methods such as Visual Inspection Analysis (VIA), Acoustic Emission (AE), and Ultrasonic Testing (UT) have been effective for in-situ crack analysis but come with limitations in terms of cost, labor intensity, and accuracy in complex environments. Digital Image Processing (DIP) and Visual Inspection (VI) provide a more affordable alternative for initial crack detection, but they lack automation and real-time adaptability. The emergence of AI-based approaches, particularly Machine Learning (ML) and Deep Learning (DL), has significantly improved crack classification and detection efficiency. ML-based models rely on feature extraction from images and datasets, whereas DL methods process raw input data to automatically learn and classify cracks with high precision. These AI-driven solutions minimize human intervention, enhance detection accuracy, and accelerate the monitoring process in Structural Health Monitoring (SHM).

Despite its advantages, AI-based SHM still faces challenges such as data scarcity, model generalization, computational constraints, and integration with existing monitoring

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frameworks. Overcoming these issues requires advancements in data augmentation techniques, transfer learning, and hybrid AI-physics models to improve accuracy and adaptability. The integration of AI with traditional SHM methods can create a more reliable and cost-effective approach for crack detection and classification. Future research should focus on developing explainable AI models and optimizing real-time processing capabilities to facilitate large-scale adoption. By addressing these challenges, AI-powered SHM can revolutionize structural assessment, enhancing safety, efficiency, and preventive maintenance strategies in civil infrastructure.

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