International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(22s) 2026 pp. 1003-1035
https://doi.org/10.70917/ijcisim-2026-5498
Article

AI-Assisted Hybrid Deep Learning Framework for Early Micro-Crack Detection and Durability Monitoring in Sustainable Concrete

Pearlin CP[1], Sheena AD[2*]

[1]Research Scholar, Department of Civil Engineering, Vels Institute of Science, Technology & Advanced Studies (VISTAS), India; cppearlin@gmail.com
[2]Department of Civil Engineering, Vels Institute of Science, Technology & Advanced Studies (VISTAS), India; sheena.se@vistas.ac.in
*Correspondence: sheena.se@vistas.ac.in

Abstract: Micro-crack initiation represents the earliest measurable indicator of durability degradation in concrete infrastructure and significantly influences long-term service life and structural reliability. Detecting sub-millimeter cracks (<0.3 mm), especially in sustainable and self-healing concrete with supplementary cementitious materials, remains challenging due to heterogeneous surface textures and environmental noise. Conventional convolutional neural networks frequently struggle to distinguish fine crack morphology from visually similar artefacts, such as scratches and aggregate boundaries. This study introduces a hybrid YOLO–Variational Quantum Classifier (VQC) framework for enhanced micro-crack detection and refinement. The YOLO stage enables real-time crack localization to maintain high recall, while extracted features are mapped into an expanded Hilbert space using angle encoding within an 8-qubit quantum circuit, allowing nonlinear geometric separation without explicit polynomial feature expansion. Entanglement operations capture higher-order inter-feature correlations, and variational parameters are optimized through gradient-based learning to construct adaptive nonlinear decision boundaries. Experimental evaluation on 8,500 annotated concrete surface images demonstrated that the proposed architecture achieved Precision = 0.94, Recall = 0.95, and F1-score = 0.95, outperforming CNN (0.84), ResNet-50 (0.87), standalone YOLO (0.92), and YOLO with classical refinement (0.93). The hybrid model reduced false positives while maintaining detection sensitivity. This framework supports predictive durability assessment, service-life modeling, and lifecycle-oriented management of sustainable concrete infrastructure, contributing to AI-driven innovation in concrete technology and construction material engineering.
Keywords: Structural health monitoring; Micro-crack detection; Sustainable concrete; Variational quantum classifier; YOLO; Deep learning; Durability assessment; Self-healing concrete; Predictive maintenance; Quantum feature mapping

1. Introduction

Modern civil infrastructure is composed of a basic material known as concrete which forms the structural foundation of bridges, buildings, tunnels, dams, pavements, and industrial facilities. Concrete, though a material of high compressive strength, is a brittle material and cannot withstand microstructural damages under mechanical load, environmental exposure, shrinkage and thermal stresses. The cracks do not typically appear in the macro-scale, yet they happen at the level of discontinuities on the cementitious matrix which are microscopic. Such micro-cracks are commonly less than a few tenths of millimetres in width and tend to arise due to redistribution of internal stress, shrinkage due to hydration, restrained deformation, or temperature gradient at early ages.

Micro-cracks may not be visible immediately but they are the initial indicators of distress in the material. They alter the local forces of stress and reduce the rigidity of the regions concerned in a calm manner. These small cracks form a network with time which enhances further spreading of crack by cyclic or sustained loading. Such mechanical stresses, freeze-thaw, chemical treatments such as sulphate attack and expansion of steel reinforcement due to corrosion tend to be the factors which lead to transition of micro-crack to macro-crack. The wider the crack then the lower is the load-bearing capacity and the structural reliability.

Micro-cracks also have a significant role in defining the permeability characteristics of concrete other than the mechanical implication. The discontinuities of hairlines are even the preferential paths to the permeation of the protective covering of concretes by water, chlorides, carbon dioxide and aggressive ions. The ingress has the effect of accelerating the rate of reinforcement corrosion which forms extensive internal forces which lead to delamination, spalling and long-term wear. Thus, micro-cracking does not occur in the surface layer but is an antecedent of durability failure. It is important to structural integrity that early diagnostics of the defects is possible to prevent service life and avoid expensive rehabilitation procedures. With infrastructure management infrastructure, detection of the start-up or early detection of micro-cracks would prevent the philosophy of maintenance to change towards preventive maintenance. Preventing the internal damage can also be achieved by identifying the cracks at the initial stages, and their corrective measures can be applied before the damage becomes rampant. Thus, good micro-crack sensors are critical components in the structural health sensing strategies in the contemporary era.

To address the problem of life span posed by cracking, researchers have developed self-healing concrete buildings that have the ability to self-heal small cracks. They utilize bacteria-based healing factor, micro-encapsulated polymer or crystal admixtures that are used as innovative materials. As the cracks grow and the water enters the matrix, the factors involved in the healing process react by depositing binding compounds which are primarily calcium carbonate or polymeric compounds that block the crack and restore the permeability.

Despite the tremendous influence on the durability aspect, self-healing technologies highly depend on the time and size of cracks that are detected. The healing mechanisms are most efficient when the cracks widths are in a fine scale most commonly on micro-scale level. At a critical level when the cracks develop, recovery is partial and structural performances cannot be fully obtained. Practically, though, the cracks are not always seen until they become visible, or structurally bad, in which case the internal deterioration process may well have advanced. This disadvantage points to the necessity of intelligent monitoring systems capable to identify the micro-cracks as soon as possible. Such systems must be capable of making high-reliability differentiations on whether a structural discontinuity occurs, and whether a surface anomaly, stain, or a change of texture is present. What is more, the crack detection cannot be called a separate diagnostic activity. Instead, it should be integrated with a monitoring logic, able to measure the thickness of cracks, their width restriction, and space resolution to determine whether or not the healing processes can be triggered.

By means of the introduction of automated crack detection and threshold-based decision making, one can make concrete buildings not only passive but as vigorously monitored. Predictive maintenance, sustainability and optimization of lifecycle becomes concentrated on early and precise detection of micro-cracks. Therefore, powerful detection schemes are needed to achieve the greatest potential of the self-healing concrete technologies.

The past decade has experienced a tremendous success in the automated crack detection by applying computer vision and deep learning techniques. CNNs, and residual neural networks have demonstrated decent performance in identifying visible cracks on different concrete surfaces, as well as object detection systems such as YOLO. These architectures gain hierarchical spatial qualities, and this permits robust localization and categorizing in complicated settings.

However, the detection of micro-cracks offers special issues which unveil the underlying vulnerability of conventional approaches to deep learning. The simplest issue is the representation of features in the normalising Euclidean space of vectors. The primary aspects that CNNs use to extract meaningful features are the gradient strength, contrast variation and discontinuities in textures. Smaller micro-cracks with a dimension of below 0.3 mm have very weak gradients and weak contrast as compared to the adjacent surfaces. Therefore, their features may be mixed with the noise of the background or minor texture variations.

It also has the problem of confusion of texture. The natural features of the concrete surface are the pores, aggregates patterns, building joints, curing marks and shadows. Such innocuous appearances frequently get mixed up with cracks that lead to high false positive by classical models. It is also difficult to determine reliability due to lighting differences, moisture lines and coloration of the surface. More profound architectures, transfer learning and data augmentation can somewhat mitigate such issues, but introduce further complexity to computation, and are not asymptotically able to mitigate these issues. This implies that the sub-millimetre cracks cannot be observed by a representation mechanism which can only represent the generic nonlinear correlations of standard convolutional feature extraction. Other computational paradigms are necessary to improve discrimination at fine levels of resolution in contrast to the classical spatial feature mapping.

Quantum machine learning suggests a fundamentally new system of representation and data classification. As an alternative to encoding features in classical vector space, the input data can be encoded as quantum states in a high-dimensional Hilbert space. The feature interaction is enabled by the parameterized quantum circuit and the features interact through the property of superposition and entanglement enable the interaction of features to form richer complex probability amplitudes, and in this way, the advantages of nonlinear reparability are localised.

This is a future benefit where micro-crack is concerned. Any small variations in the pixel intensities that are not apparent when using classical linear or convolutional transformations can be better viewed when the pixel intensities are represented in the form of quantum states through the assistance of rotation based encodings. All classical feature values can then be represented as qubit rotation parameters, which are image patches in exponentially larger representational spaces. Layers The entanglement layers allow the qubits to be correlated, such that the joint feature interactions can be efficiently modelled.

Even more flexible are the variation quantum classifier (VQC) which permits the optimization of the trainable parameters of the gates by means of hybrid classical-quantum learning. Measurement outcomes provide probabilistic classifications influenced by quantum interference patterns, and augmentation of the process of separation of authentic micro-cracks and visually identical artefacts. It is important to note that quantum models are not suggested as being alternative to classical systems on their own. Instead, a combined approach introduces a localization effectiveness of deep learning and enhances the reparability of quantum feature mapping. It is a new direction to implement such a hybrid approach to the structural health monitoring. The system is intended to have the ability to pick up finer discontinuities by patch-level quantum validation of classical detection and be computationally feasible. This synergy brings about new possibilities of smart infrastructure inspection.

The primary objective of the intended project is to develop a smart and reliable solution to an issue of the early micro-cracks identification in concrete structures through the combination of standard computer vision with quantum machine learning. The weaknesses of the standard deep learning models that do not identify the sub-millimetre scale cracks and tend to identify surface texture, stains, and changes in lighting as defects will be addressed with the proposed system.

Specifically, the framework combines an object detector using the YOLO framework to identify cracks with a high degree of efficiency with a variation quantum classifier to reject the patches that are discriminated on a higher level. The classical step ensures quick and precise finding of candidate crack locales and the quantum step tends to give a more refined categorization of the high-dimensional feature encoding and entanglement-based nonlinear separation. The objective of this combination is to make the detection sensitive and meanwhile to reduce the false positives.

Among the secondary objectives, the connection of the crack detection and proactive monitoring strategies is to be provided. The system does not just end by classification but rather it passes the outputs of detection into a monitoring logic which is an activation of a threshold that should self-heal. The framework evaluates the density and the width of the crack threshold and makes a decision on whether autonomous healing is on or off. This incorporation transforms the passive inspection strategy into the predictive maintenance.

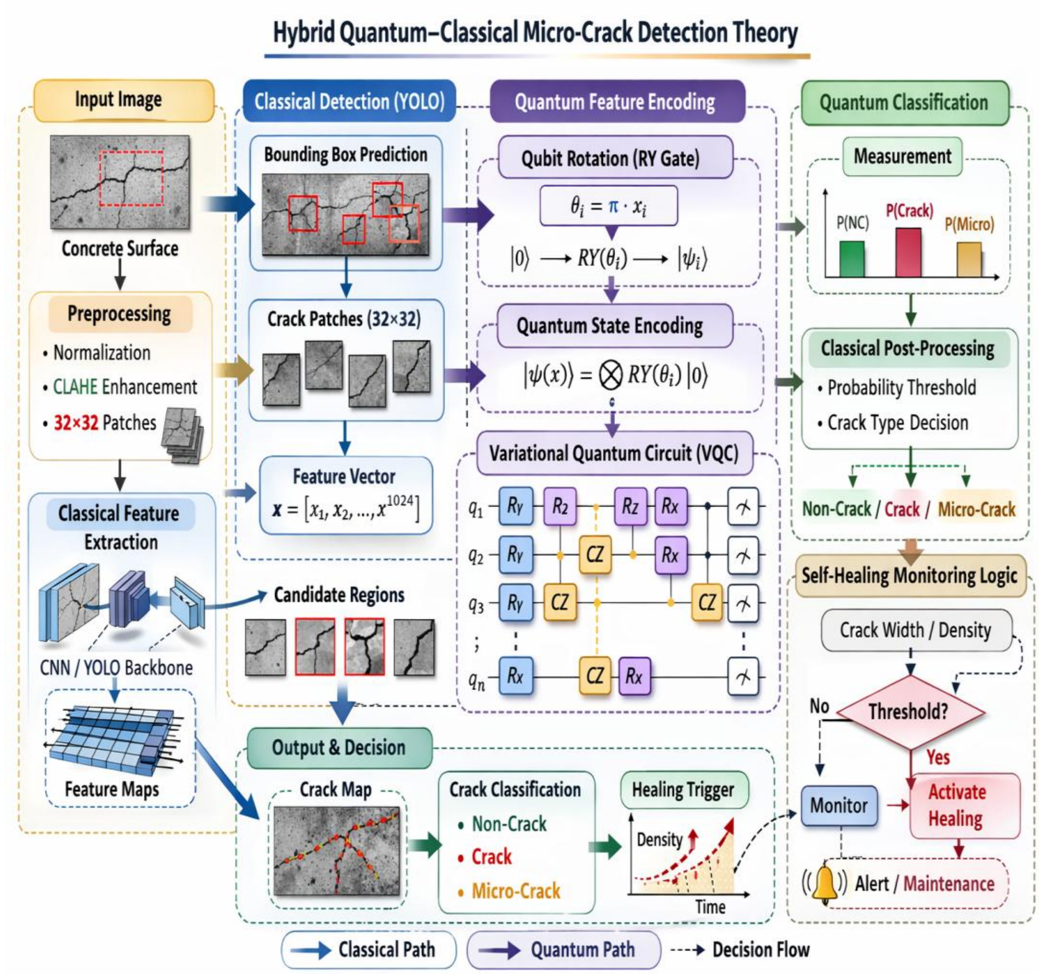

Figure. 1. Conceptual diagram of the proposed system

Moreover, the paper shall also demonstrate, a realistic implementation of hybrid quantum-classical learning in civil infrastructure in the near future. It is not directed at the replacement of classical models but intended to enhance these models with quantum validation at patch scale, rendering them computationally possible. Finally, the proposed project is intended to contribute to rendering concrete construction more safe and sustainable since it will provide the opportunity to intervene at an earlier stage, improve the durability management process, and contribute to the smarter infrastructure monitoring system.

The principal contributions of this paper are summarised as:

- Design of a hybrid quantum-classical crack detection system that has the ability to enable early micro-crack detection.
- Addition of a quantum validation layer that is a variational quantum classifier to further dissociate the fine discontinuities.
- Implementation of a self-healing monitoring logic that links with crack detection outputs and the logic is employed to implement predictive maintenance decisions.
- End to end performance of the experiment with regard to classical CNN and object detectors.
- Indication of imminent practical quantum application in the infrastructure monitoring of the civil.

2. Literature Review

2.1 Evolution of Vision-Based Crack Detection

The study conducted in [1] demonstrated that among the earliest convolutional neural networks (CNNs) applications, there were crack detection in concrete buildings using automated techniques. The authors were able to show that CNNs can extract hierarchical crack features directly using raw image without feature engineering. They found that they were more resistant to background noise and texture variation compared with the traditional filtering techniques. In [2], classical methods of edge detection and deep CNNs models were compared. According to the study, both Sobel and Canny operators are extremely sensitive to the illumination and surface irregularities change. Deep models were however more concurrent in varying conditions of the environment. The article in [3] made use of deep convolutional architectures by direct application to the road crack segmentation. Pixels were also detected in the model as opposed to the basic classification schemes and this made the model more precise in mapping the geometry of the cracks. This led to an improved structural assessment process.

The multi-damage of concrete structures was also detected using fully convolutional networks (FCNs) in [4]. The research was not restricted to detecting crack but also other structural defects were taken into consideration. Localization was more accurate in dense segmentation and false detections were reduced in the system. A real time object detection paradigm was introduced in the single stage regression in the suggested unified detection architecture in [5]. Although the initial goal was general objects, it was the foundation of applying YOLO based on models of crack detection. It was suitable as far as speed in infrastructure inspection was concerned. Based on this, [6] maximized the accuracy-speed trade-off and improved the detection performance. The enhanced YOLO architecture was more effective at the localization of small objects, which is required when localizing fine cracks. This invention improved cracks monitoring at the field level.

In [7], the literature review of the transition of traditional image processing to the deep learning methodology was conducted within the framework of civil infrastructure monitoring. Such challenges as the imbalance of datasets and environmental noise were mentioned in the authors. Their synthesis was useful in illuminating the future study of automated inspection. The study of [8] has been on predictive maintenance techniques where the artificial intelligence is applied. Rather than focusing on the detection component, it associated defect recognition with long-term infrastructure health management. This system-level outlook extended opportunities of AI on structural monitoring. In [9], a study determined machine learning techniques in structural health monitoring systems. The authors brought up the evidence-based approaches of detecting the anomalies in infrastructure. They discovered that intelligent decision support systems are important.

2.2 Emergence of Quantum Machine Learning Concepts

In [10], the background introduction explained the way in which the idea of quantum computing (superposition and entanglement) could be implemented in order to enhance the machine learning processes. Potential computational advantages in the pattern recognition tasks were suggested in the research. It provided the theoretical explanation of the quantum-enhanced data processing. Enhanced feature space quantum in [11], quantum enhanced feature space was suggested as a model of supervised learning. The authors have demonstrated that feature separation can be improved through mapping classical data in Hilbert space. This attempt gave better degrees of classification experimental data. In [12], they talked about neural network analogue trainable models as parameterized quantum circuits. The researchers have shown that gradient-based techniques are applicable in optimization of such circuits. It showed the variational quantum classifiers.

The overview described in [13] was an opinion of the overall relationship between quantum algorithms and machine learning applications. The authors investigated different algorithm paradigms which may be applied to quantum hardware. The concept of physics and AI relationship was strengthened in this paper. The variational quantum algorithms were also mentioned in [14], as applied to the noisy intermediate-scale quantum (NISQ) machines. The article addressed the problem of practice implementation and optimization. It also stressed the ability of hybrid models to be flexible when hardware constraints arise. Hybrid classical-quantum learning models were also applied using the neural networks on quantum circuits in [15]. The experiment revealed that quantum classifiers could be used with classical feature extractors. This hybrid solution boosted interoperability with the already existing deep learning pipelines.

2.3 Crack Monitoring and Self-Healing Materials

T The curing process proposed in [16] was based on the concept of bacteria-based curing, alienation of microbial mineral precipitation through which microbial autonomous crack sealing is attained. The researchers proved that micro-cracks can be closed in the instance of bacteria activation in a wet environment. This pioneered the building materials which were sustainable. In [17] experimental fracture-based healing assessment was used to measure efficiency of crack closure. In the research, mechanical strength recovery after healing was provided in the form of quantifiable data. It proved that self-healing systems are structurally sound.

Aggregates Encapsulation methods were explored in [18] in relation to the concept of the addition of the healing agents to aggregates. The reason is that the study improved the dwell time by applying healing materials until the formation of cracks. This partial activation plan resulted in the enhancement of the long term performance. In [19], the literature review was broad in terms of covering self-healing in cementitious materials. It categorized the ways the healing mechanisms could be categorized and their efficiency limits were mentioned. It is noteworthy that it emphasized the need to do crack in the early detection. The reviewed structural monitoring systems in [20] were based on AI. The study indicated the combination of smart technologies and smart analytics. However, it has also cited the inexistence of advanced micro-crack-specific detectors.

2.4 Advanced Deep Learning for Crack Classification

The multi-stage YOLO-ViT framework proposed in [21] used transformer attention mechanisms and object detection. This composite design helped in the contextualization of crack textures. It was more competent in categorizing deviant cracks patterns. The research on the deep learning-based crack detection method was experimented in the controlled laboratory conditions in [22]. These authors had been very specific and gave reports of poor performance in field variability. This brought to the fore realistic generalization challenges.

Good multi-damage detection was optimized by making enhancements to YOLO architectures in [23]. The new anchor design was more enhanced in terms of detection of small structural defects. The article optimized the object recognition in infrastructure. The illumination problems during the crack imaging process were solved using the [24] light integration approach. The depth information and deep learning were added to enhance reliability of the detection. This plan reduced the number of false positives caused by surface shadows. The model [25] was directed at the identification of fine cracks with the assistance of advanced feature derivation algorithms. The research increased micro-cracks sensitivity, although it was limited to classical calculation. It placed emphasis on the difficulty in distinguishing fine cracks patterns and noise.

2.5 Hybrid Quantum-Classical Learning for Image Analysis

The benefits of the image classification task of the hybrid quantum-classical vision model were recorded in the nonlinear mapping of the image classification task in [26]. The study was able to offer a hypothesis that quantum layers could enhance feature transformation. This has offered the chances of micro-pattern detection. Hybrid networks have been comparatively analysed in [27] with the purely classical models. Results depicted performance improvement under some circumstances. Hardware constraints were identified, though. Variational shadow quantum learning proposed measurement-efficient ways of classification [28]. The strategy made it possible to reduce the computational loading without compromising precision of the model. It was offering scalable hybrid systems.

Eventually, it was confirmed that the end-to-end hybrid classifier described in [29] was compatible with gradient-based optimization. The architecture allowed the easy way of integrating it with the traditional training structures. This increased reality of deployment. The quantum hybrid models on complex data were extensions of multi-class hybrid classification that was studied in [30]. The research showed consistent findings across over one class. It focused on the possibility of scalability. Variational quantum neural networks that are verified in [31] were found possible in a simulated environment. It was shown in the experiment that the separation of nonlinear groups of data was better possible. It supported the application of quantum classifiers to problems of images. A summary of quantum tools to visual classification was provided in [32]. It categorized different circuit designs and encoding strategies. The study provided a roadmap of implementation.

In [33], a variational quantum architecture was optimized to classify problems. The problem of over-parameterization was discussed in the study. It also increased the stability in training. The hybrid quantum-classical CNN model used in [34] had the convolutional feature extraction process and quantum decision layers. Complex image data had greater separability in benchmark tests. This tested the hybrid architectures. Scalability and design limits in quantum systems of learning were covered in [35] in terms of survey analysis. It concentrated on the algorithm-hardware co-design. The research directions of the future were pointed out in the paper. The analysis of the expressive power of quantum neural networks theoretically was performed in [36]. The authors showed that their methods had potential computational advantages in comparison with classical networks. This increased the driving force of hybrid systems.

This variational solver is available in [37]. It determined that photonic processors can be applied to implement hybrid algorithms. This defined the viability of the experiment. The former strategies addressed barren plateau problems of quantum circuits in [38]. The research improved the meeting of training. This is important in the design of quantum classifiers in a stable manner. In [39], it was found that the distribution learning was explored in quantum generative adversarial methods. The study indicated the well-developed data encoding techniques. Such processes would assist in the anomaly -model in crack detection. And finally, quantum dimensionality reduction is suggested in quantum principal component analysis in [40]. The experiment showed faster derivation of salient features. The technique is helpful in high dimensional crack images.

Recent developments in structural health monitoring (SHM) increasingly utilize deep learning techniques to improve automated crack detection and durability assessment in concrete infrastructure. Approaches based on deep learning, such as convolutional neural networks and attention-enhanced detection architectures, have demonstrated robust performance in identifying fine surface cracks under challenging lighting and heterogeneous texture conditions [41]. Comprehensive reviews indicate that vision-based artificial intelligence systems are being integrated into infrastructure inspection workflows to facilitate predictive maintenance and lifecycle management strategies [43].

At the materials scale, machine learning models have been effectively applied to predict the mechanical performance and durability characteristics of sustainable concrete systems that incorporate supplementary cementitious materials and fiber reinforcement [44]. However, distinguishing sub-millimeter micro-cracks from visually similar artefacts, such as surface scratches and aggregate boundaries, remains a significant technical challenge, especially in heterogeneous and sustainable concrete surfaces. These findings underscore the necessity for hybrid learning frameworks that can improve nonlinear feature separability while preserving engineering relevance for durability-focused evaluation and intelligent infrastructure monitoring.

2.6 Research Gap

Although the research [1]-[9] has contributed a lot to the vision-based crack detection, it is restricted to the classical limitations of feature representation. The theoretical foundations of quantum-enhanced learning were established in [10]-[15] however the research did not target the implementation to the civil infrastructure. The content of research in [16]-[20] has highlighted the significance of crack detection in the beginning but it has not been combined with sophisticated calculation. The advanced models in [21]-[25] are classical convolutional architecture mainly and can be affected by noise in the environment. Also during this period, hybrid quantum algorithms of [26]-[40] operate primarily on benchmark image data, rather than structural defects of the real world. In this way, there exists an apparent vacuity on the interface between micro-crack identification, mixed quantum-classical authentication, and smart structural surveillance. Combining YOLO-based detectors with variational quantum classification would possibly be even more separable of minute patterns of cracks, and could be used in real time.

The proposed work per se is a direct response to the research gap identified because it integrates the high level of detection intelligence with the sustainable self-healing material technology into a system response. According to the existing literature on classical deep learning, the accuracy of crack detection is used, but the separation of micro cracks in complicated surface conditions is ignored, and on the other hand, quantum learning literature is formed on the basis of benchmark data sets rather than on the basis of practical infrastructure application. Simultaneously, self-healing concrete research is concerned with material performance and is not equipped with smart and automated crack monitoring.

The proposed system will bridge this disconnect between these realms, between the YOLO-based real-time localization of cracks and a Variational Quantum Classifier (VQC) to advance the classification of micro-crack patterns. At the same time, the mixture of bamboo fibres, ribbed husk ash (RHA), herbs additives, and bacteria-based healing agents improves the crack management, strength and environmental sustainability. The given solution is a mixture of the intelligent detection, quantum-assisted validation, and environmentally friendly curative systems, which develops an integrated, scalable, and cost-effective solution to the next-generation structural health monitoring.

Table 1. Comparison of Existing works with the proposed work

Approach / Study	**Core Strategy**	**Crack Handling Capacity**	**Eco / Cost Profile**
[1]-[4] CNN-Based Detection	Deep CNN Models	Visible Cracks Only	Moderate Cost
[5], [6], [23] YOLO Detection	Real-Time Object Detection	Small Crack Loss	Fast, Scalable
[16]-[19] Bacteria SHC	Bio-Mineral Precipitation	0.2-0.5 mm	Eco-Friendly, Costly
[17], [18] SAP / ECC Systems	Fibers + SAP	<200 µm	Durable, Expensive
[21], [22], [25] Advanced DL Models	YOLO + Transformer	Fine Crack Detection	High Accuracy, Costly

3. Methodology

The proposed structure health monitoring system is designed in the hierarchy, end-to-end pipeline, including sensing, intelligent detection, quantum-enhanced validation and automated maintenance based decision-making. It is initiated by the acquisition of high-resolution images on an installed fixed platform, handheld platform, or flying unmanned platform, which is based on calibrated digital imaging systems. Processing of images to minimize environmental perturbations due to change in light, water on surfaces or shadowing effects is done by use of contrast, noise reduction, geometric, and intensity equalization. The enhanced images are then forwarded to a deep learning object identification component that is built on a YOLO framework.

YOLO network is a one-stage detector which classifies a grid of the image and predicts an area of the possible cracks and a confidence measure of the possible cracks. This architecture can be localised in real time, yet retains the spatial precision. The idea of non-maximum suppression is employed to eliminate the overlapping detections and retain the most appropriate ones of cracks. The local regions are subsequently cut into a constant size, and the normalization and resizing done to get uniform input tensors. This step-wise extraction is a guarantee that only meaningful items are forwarded to the classification stage and therefore, redundancy of computations is reduced and fine-scale structural characteristics would be separated to processing.

The second step is crack patch transformation that converts the minuscule sized crack patches into smaller numerical values that can be quantum encoded. The patches are squashed or pressed through a feature compression layer of light weight to generate normalized vectors that are of value between 0 and 1. The classical features are then encoded to quantum states through angle encoding such that every element of the feature determines the angle of rotation of a qubit using parameterized rotation gates. It is this encoding that maps data to a high-dimensional Hilbert space, the dimension of which grows exponentially with the count of qubits. Once the encoding has been done, the encoded state is executed on a variational quantum circuit, which is a sequence of alternating layers of trainable single-qubit rotations and entanglement gates. The processes of entanglement construct statistics between features which enable the circuit to model the more complex interdependences such as crack continuity, coherence of orientation, and intensity fronts. The optimization of the variational parameters is carried out using a hybrid classical-quantum loop which aims to minimize a classification loss. In case of the expectation values measurement, probabilistic outputs are obtained which indicates whether patch is a micro-crack, a surface mark, or a noise artifact, enhances the discriminative accuracy.

The outputs of the variational quantum classifier are the probabilities that are once again used in the traditional pipeline in the assessment of structural condition. The result of the patch-level classification of any patch is spatially mapped back to the relative position of the patch within the original image and a profile of a crack distribution across the entire surface checked can be reconstructed. Crack density is obtained by obtaining the total number of pixel crack that is validated divided by the area that was inspected, and crack width is obtained by pixel to millimetre calibration provided by the imaging resolution parameters.

The engineering levels are also predetermined to determine the levels of the severity to establish the hairline micro-cracks, moderate discontinuities, and critical areas of damage. Statistical filtering applies to the system to remove cases of isolated false detection, and time consistency checks in cases that can be sequentially checked. This causes the short term artefacts not to be perceived as a kind of slow deterioration. The framework integrates quantum-refined classification and spatial aggregation to provide a powerful and quantitative structural health index rather than the single-location detection results.

The final step is an intelligent predictive maintenance layer that will be resorted to in order to activate bio-inspired self-healing when the state of the structure is out of the acceptable safety levels. A maintenance warning or an automatic healing system is triggered in case the density of the crack or the average width is too great of the predetermined limits. The curing process uses green fabrics such as bamboo fibres to fill cracks so as to strengthen them, rice husk ash (RHA) to increase pozzolanic behaviour and densification of the structure, herbs, to improve durability properties and bacteria-based mineralisation agents to precipitate calcium carbonate in cracks.

When water is added to micro-cracks observed, the microbial activity is activated and the discontinuities are sealed and the minerals deposited. The framework transforms passive inspection to active infrastructure management since the logic is linked to the output of detection to initiate the healing. This type of closed loop design also ensures that errors at the early phases are not only easily detected at high sensitivity but also corrected before it turns to macro-level structural errors and hence, it enhances longevity, less usage of resources in maintenance and long term functionality of infrastructure.

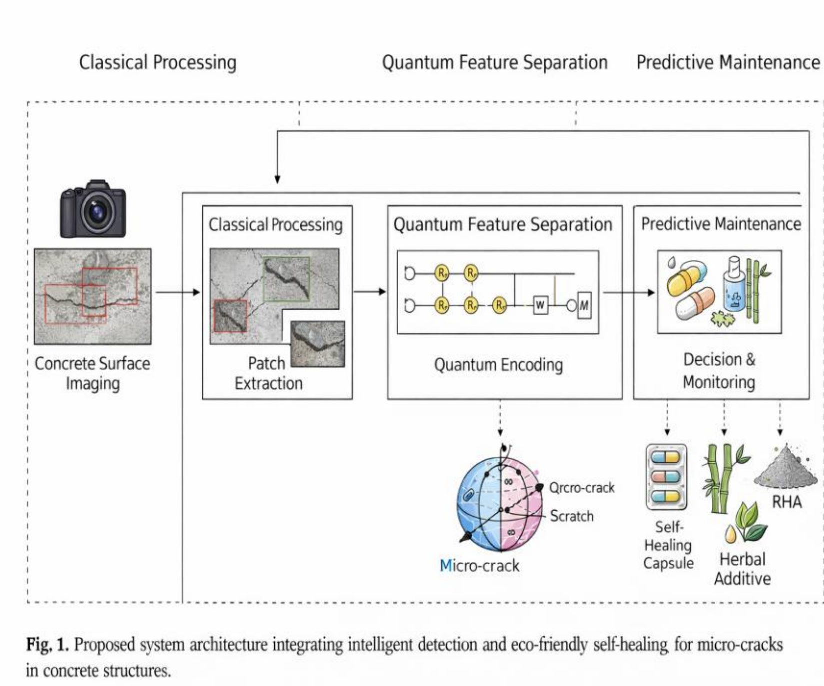

Figure. 2. System Architecture Diagram

3.1 Image Acquisition and Preprocessing

The training and evaluation database consists of pictures of concrete surfaces which were captured in publicly available crack repositories, and in controlled laboratory samples. The images differ in terms of light intensity, texture of the surface, thickness of breaking cracks and noise in the surrounding to give strength to the model. The image resolves are normally 512 512 to 1024 1024 pixels that is adequate to show the fine crack structures. Contrast limited Adaptive Histogram Equalization (CLAHE) is employed in order to make the thin crack patterns more visible. Unlike conventional histogram equalization, CLAHE amplifies local contrast, but does not enhance noise, a particularly important quality when one needs to observe micro-cracks of the textured surface of the concrete. Contrast enhancement is followed by resizing the images to the Yolo input dimensions of 640 640.

Data augmentation techniques that are employed to improve the generalization capacity and reduce overfitting are horizontal flipping, change of brightness and random rotation. Due to crack detection, the areas of the bounding box are reduced to small patches (e.g. 64 64 or 128 128 pixels). Such an operation separates the information relevant to crack and makes the computational complexity of quantum encoding less complicated. Every patch is mapped to the range [0,1] and transformed back to an expression of feature vectors that may be used to represent quantum states. This pre-processing pipeline normalizes input data, enhances micro-crack contrast and ensures compatibility of classical processing steps with quantum processing steps on a structured basis.

3.2 Classical Detection Stage

The crack localization module is created on the premise of a customized YOLO architecture that specializes in long crack detection. The backbone network acquires hierarchical information on the convolutional layers and the neck generates these spatial and semantic information at the various levels. Bounding box regression Object classification is performed on the same detection head.

Transfer learning is performed through the initialisation of the model using pre-trained weights and fine-tuning of the model with crack-specific datasets. The strategy enhances the convergence speed and performance on small data. The k-means algorithm to optimize the anchor boxes is done on the basis of annotated ground truth bounding boxes. The cracks tend to be thin and lengthy, that is, the size of an anchoring is transformed in order to increase the localization sensitivity.

The total loss takes into consideration three factors:

1. Bounding Box Regression Loss (CIoU Loss)
2. Objectness Loss (Binary Cross-Entropy)
3. Classification Loss

All these losses optimize spatial accuracy and detection confidence.

Table 2. YOLO Hyper parameters

Parameter	**Value**
Input Size	640 × 640
Batch Size	16
Learning Rate	0.001
Optimizer	Adam
Epochs	100
Confidence Threshold	0.5
IoU Threshold	0.5

Classical detection stage is characterized by high recall with visible cracks and also may be used as a region proposal mechanism in quantum refinement.

3.3 Quantum Feature Encoding

After the extraction of patch, the normalized patch of any image is a transformed feature:

$$x = [\, x_1, x_2, \ldots, x_n \,] \qquad (1)$$

Each feature x_i is mapped to a quantum rotation angle:

$$\theta_i = \pi \, x_i \qquad (2)$$

The reason behind this scaling is to ensure that normalized pixel values are scaled into rotation parameters in the range [0,pi]. The coded quantum state is represented as:

$$|\psi(x)\rangle = \Pi_i R_Y(\theta_i)|0\rangle \qquad (3)$$

R Y i i is the qubit rotation around the Y-axis of the i th qubit. It is this quantum Hilbert space mapping of classical data which enables classical data to be modelled as a superposition. High-dimensional quantum state is used to increase the discriminative capacity of detecting fine crack patterns and noise artefacts. The encoded state is then transformed to pass through the parameterized quantum circuit to be classified.

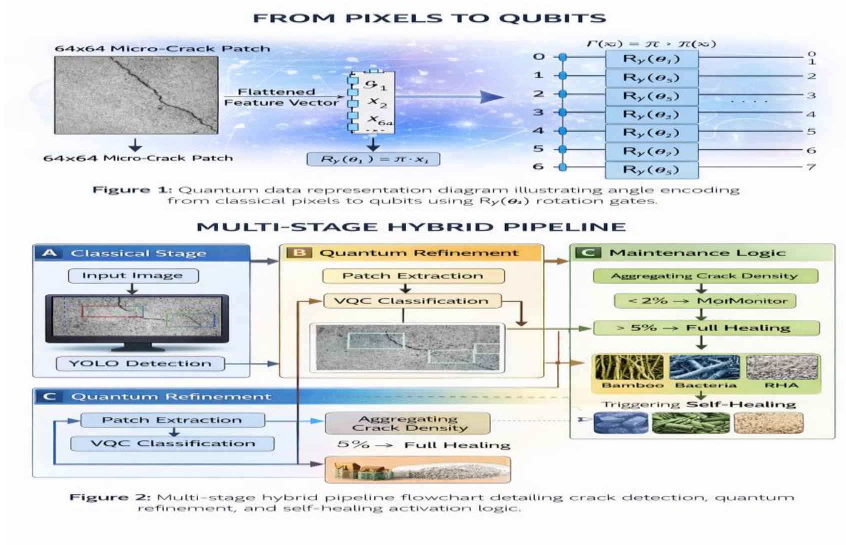

Figure. 3. Quantum Data Representation Diagram

3.4 Variational Quantum Classifier (VQC)

Variational Quantum Classifier is a series of parameterized rotating gate and entanglement operations. Each layer is followed by single-qubit rotations (R Y and R Z) followed by entanglement through Controlled-NOT (CNOT) gates. The expressiveness and stability trade-off during training usually involves a trade-off between the choice of circuit depth of 2-4 layers.

The entanglement is arranged in linear or circular geometry to symbolize the association between the surrounding features. The circuit parameters are optimized with the help of the gradient based methods such as Adam that helps to reduce the cross-entropy loss between the predicted and true labels. Measures are carried out on the computational basis. The expectation value of Pauli-Z operator produces the probability of the classes:

$$P(class) = 1 + \langle Z \rangle / 2 \qquad (4)$$

This output of probability is also extended to the monitoring system to assess its severity.

3.5 Self-Healing Monitoring Logic

Bacillus subtilis B. subtilis is a predictive logic maintenance and sporing, non-pathogenic The last module is a combination of detectors and predictive logic. The seriousness of the cracks is determined by the size of the bounding boxes, the pixel intensity change and classification amount. Crack density is computed as:

Crack Density= (Total Crack Area / Surface Area) × 100 (5)

Intervention thresholds are determined in the following way:

- Density < 2% - Monitoring only
- 2 - 5% - Minor healing activation
- 5% - Full healing protocol

The healing system entails mechanical bridging with the help of bamboo fibres, reducing permeability with the help of rice husk ash (RHA), enhancing strength with the help of herbal additives, and self-healing with the help of bacteria-based mineralization. A predictive maintenance model also tracks the rate of crack propagation over time hence enabling early intervention before the structural degrading rate is boosted.

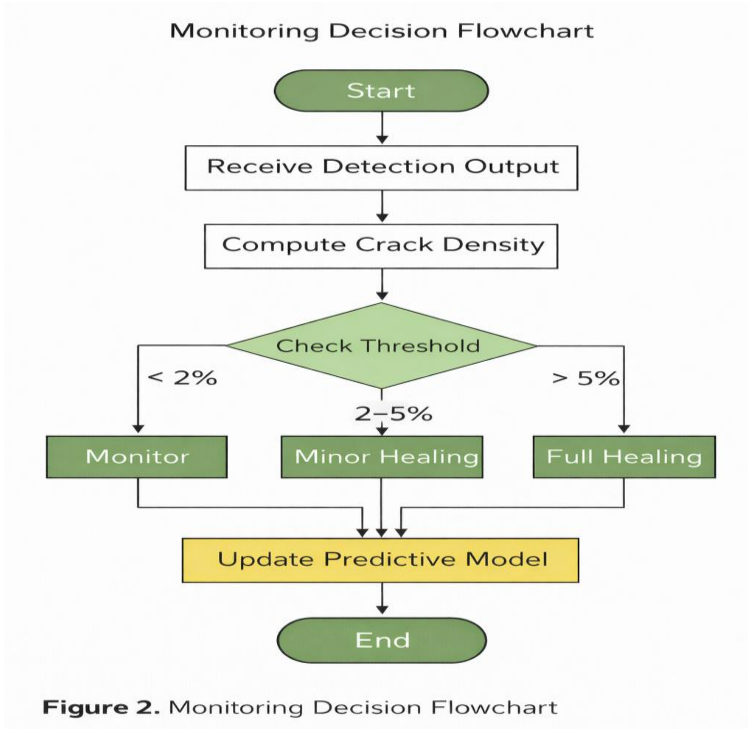

Figure. 4. Monitoring Decision Flowchart for Crack Density-Based Predictive Maintenance.

If the dataset is diverse, then there is strength in the deployment environments of the real world, but the sensitivity of micro-cracks is not lost.

4. Experimental Framework

Every component of the hybrid classical-quantum crack detection/predicted maintenance model was systematically set up in the experimental set up to verify the experiment in controlled and reproducible conditions. The pipeline was divided into four major stages, that is, dataset preparation and annotation, training and validation of classical detectors, quantum classifier design and optimization, and ultimate performance benchmarking with standardized statistical metrics. Each and every experiment was designed under the specified pre-processing protocols and controlled hyper parameter settings to make a fair comparison of the classical models and the hybrid architecture.

The classical detection module was built on a YOLO based architecture that was trained on stochastic gradient descent as well as an adaptive learning rate schedule. A variational circuit simulator was used to design a quantum classifier, in which the parameters of quantum gates are optimized by classical backpropagation through application of gradient-based algorithms. To ensure the reliability of the experimental, the dataset was stratified into training (70%), validation (15%), and testing (15) sets to ensure the all-equivalent representation of the cases of cracked, non-cracked and micro-cracks. The performance was evaluated using accuracy, precision, recall, F1-score, Intersection over Union (IoU) and confusion matrices and receiver operating characteristic (ROC). Measuring inference latency and computational runtime was also used as a measure of practical deployment. This systematic design will ensure that whatever improvements they discover in hybrid model can be attributed to a simple enhancement of an architecture, as opposed to experimental bias.

4.1 Dataset Description

The information in this work was carefully edited so as to achieve a structural heterogeneity of the real world and an environmental variability. It consists of publicly available and highly controlled laboratory measured high-resolution concrete surface images under varying illumination conditions and over various surface conditions. With the addition of laboratory data, controlled imaging of small micro-cracks in optical systems became possible, with a calibration being such that accurate ground-truth measurements of the width and morphology of cracks were acquired. Purposely diversifying the dataset to encompass numerous concrete finishes, aggregate exposures, curing marks, and surface roughness variation and environmental artefacts such as stains and shadows was also done to cover as many concrete finishes as possible. This diversity causes extrapolation of the trained models that would not be valid within the ideal environment and would not survive in the natural inspection environments. Micro-crack cases were also closely observed, i.e. the cracks in the width under 0.3 mm, since those are the manifestation of the structural degradation at the initial stage, and are much more difficult to be detected due to the low gradient contrast. There are 8,500 annotated images in the last dataset, of which 5, 200 images contain visible cracks, and 3, 300 images contain no cracks or prevailing noise surfaces. The broken group contains approximately 2,100 pictures that have micro-cracks that have been identified. Such micro-cracks were also studied under big magnification view tools using the hands and were marked with precise bounding boxes. To minimize labelling bias and inter-annotator variability, annotation consistency was performed by multi-reviewer cross-validation where independent reviewers verified presence, orientation and width of cracks by classifying them as present, absent and indeterminate.

Table 3. Dataset statistics

Category	**No. of images**	**Percentage**
Total Images	8,500	100%
Cracked Surfaces	5,200	61.2%
Non-Cracked Surfaces	3,300	38.8%
Micro-Crack Images	2,100	24.7%
Training Set	5,950	70%
Validation Set	1,275	15%
Testing Set	1,275	15%

4.2 Training Configuration

The training environment was developed very carefully with the purpose of supporting not only the computational efficiency but also the algorithmic stability of both classical and quantum elements of the framework. The classical step of detection was conducted in a high-performance workstation, the equipment of which is NVIDIA RTX series (12 GB VRAM) and 32 GB system memory and i7 processor. The tensors that were large were to be fed through the assistance of the use of the GPU to facilitate the parallelization of the convolutional operations in the forward and backward propagation. The CUDA-enabling environment could achieve stable throughput of mini-batch gradient updates through to 100 training epochs.

Pre-processing pipelines were used to optimize the use of multi-threads to ensure that the process of loading the data could not be a bottleneck in the training. The augmentation techniques included horizontal flipping, random brightness scaling, slight rotation, and normalization of contrast so that it can enhance generalization. These transformations were introduced in a probabilistic manner when training and deactivated when validating and testing so that the evaluation integrity is maintained.

The training parameters in the case of classical detection model are as follows:

- Input size: 640 × 640
- Batch size: 16
- Learning rate: 0.001
- Optimizer: Adam
- Number of epochs: 100

- Confidence threshold: 0.5
- IoU threshold: 0.5

The pre-trained weights were used to apply transfer learning and the crack dataset fine-tuned. Validation loss stabilization allowed unbiased early stopping to prevent overfitting. The Yolo-based detector was trained on a transfer learning approach, which accelerated the convergence and increased the strength of features. Pre-trained weights were used to initialize backbone convolutional layers and these were initially trained on large scale object detection data. This was started to provide generalized edge and texture detectors which were optimized on the crack-specific data. Training images had been resized to 640 × 640 to compromise modelling spatial detail with the constraints of the GPU memory. The batch size was 16 to ensure that the gradient was not estimated repeatedly and to ensure that it did not exceed the memory limits. Adam optimizer learning rate of 0.001 was adopted since it possesses adaptive moment estimation option which makes the convergence steady in the process of training on heterogeneous surface textures. The computation of losses consists of loss + bounding box regression loss, objectness confidence loss and classification loss. Non maximum suppression was then applied to inference to remove located predictions with an overlap of 0.5 with an IoU threshold of 0.5. Early stopping monitored the pattern of validation losses and stopped training when it became clear that the performance ceased to increase to benefit overfitting and allow generalization.

Once the detectors were trained, the pipeline was changed to patch extraction and quantum classifier preparation. The regions of obtained cracks were cropped according to the estimated bounding boxes and resized to 64 x 64 pixels. This resolution was selected to ensure that the cracks have a good fine morphology and at the same time enables these computations to be quantum encoded. Each patch was then converted to a feature vector and scaled to the [0,1] scale so that it could be quantum encoded via rotation.

The high rotation magnitudes that could result in circuit gradual instability were also prevented through normalization. Encoding was preceded by optional feature compression with either pooling or principal component projection, so as to reduce dimensions whilst preserving structural patterns. The resulting set of features was split into training and validation quantum classifier specific sets. Alternating care was also carried out to maintain a balance of classes among the micro-cracks, superficial artefacts and patches of noise such that optimization is not biased.

With Variational Quantum Classifier (VQC) patches identified by the YOLO were resized to 64x 64 and flattened into feature vectors. The features were standardized to the [0,1] scale and coded through the angle encoding where every feature: xi x1 = x2 = x3 was entered using:

$$\theta_i = \pi\, x_i \tag{6}$$

The circuit was a quantum circuit consisting of 8 qubits and 3 layers of variational gates including rotation gates (R Y and R Z) and the linear entanglement through CNOT gates. Circuit parameters were optimized with the Adam optimizer with a learning rate of 0.01 and 50 training cycles. The cross-entropy loss was the objective function.

Serially hybrid training was conducted on a pipeline:

1. Train YOLO detector.
2. Extract crack patches.
3. Train VQC on extracted patches.
4. Integrate probabilistic outputs into monitoring logic.

This incremental approach ensured the effectiveness in calculation and fixed convergence.

4.3 Evaluation Metrics

The designation and classification was used in the evaluation of the performance to provide a comprehensive evaluation of the framework. Normative values of finding objects and binary classification were involved so that benchmarking remains the same.

Let:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Precision is the number of the correctly identified cracks to all the cracks that were predicted. Recall is an evaluation of the ability to detect actual instances of crack. F1-score provides the harmonic meaning of precision and recall. Micro-cracks performance on the micro-crack samples is specifically measured by the micro-crack sensitivity. False Positive Rate (FPR) is the term that is employed to define the misclassification of non-cracked surfaces. The independent test size of 1,275 images was tested. Detection stage performance was assessed using the assistance of the IoU-based matching with a 0.5 threshold. Patch-level predictions derived were tested on the quantum classifier.

The general system behaviour in terms of end to end accuracy of localization of micro-cracks, classification and transmission to predictive monitoring module were evaluated. The issue of micro-crack sensitivity was also taken into consideration with special care given because the concept of early-detection is very important in preventive maintenance techniques. Classical high-recall detection was combined with quantum enhanced feature discrimination, which produced improved noise artefact resistance and scratch resistance on the surface. The misjudgement of the false positives was reduced at the classification level and the structural thresholds were the only ones actual violated so as to activate self-healing mechanisms.

4.4 Experimental Workflow

he data preparation phase is an end-to-end systematically organized experimental pipeline that begins with the preparation of unprocessed concrete surface images, curation, bounding box labelling of the crack regions (including micro-cracks), stratified sampling to training, validation, and testing subsets. This is then followed by applying Contrast Limited Adaptive Histogram Equalization (CLAHE) that is applied in order to better the images to boost the local contrast and amplify the thin crack patterns and minimize the increase in noise. These enhanced images are then lowered to a steady resolution (640 640) to input into the YOLO-based identification framework to be prepared with the supervision to be taught with the best hyper parameters and anchor box configurations to fit the elongated crack geometry. With training, the YOLO takes the position of localizing the cracks, by identifying the bounding boxes with confidence measures and Intersection-over-Union (IoU) filtering.

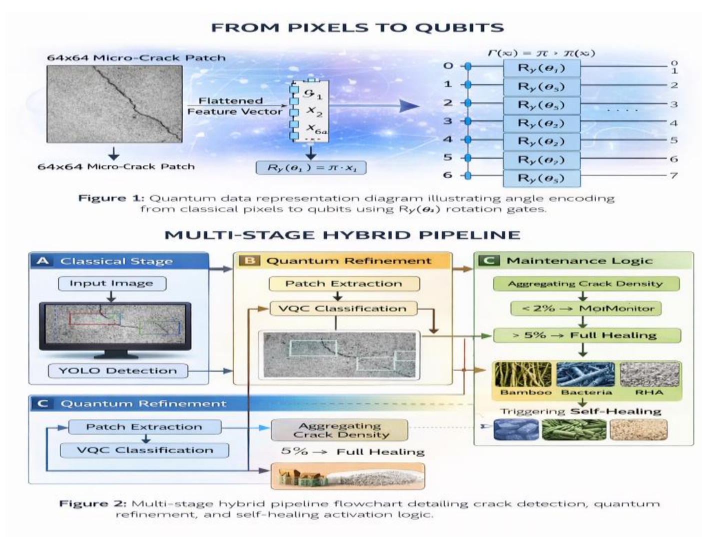

Figure. 5. Multi-Stage Hybrid Pipeline Flowchart

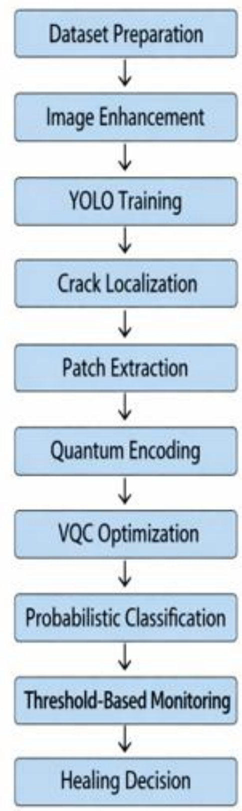

Figure. 6. Flow chart of the proposed work

The found cracks are sliced into smaller fixed-size patches (e.g. 64 x 64), but resampled to the level of [0,1], and flattened to structured feature vectors. Angelic encoding these classical properties into quantum states the angle encoding gives a parameter of rotation 0 =/iqx i that is the output of applying the mapping to each normalized feature x i to a rotation parameter 0 i=pi xi. Encoding states are then fed into a Variational Quantum Classifier (VQC) which consists of an ensemble of rotation gates and entanglement operations, the trainable parameters of which are optimized to minimize cross-entropy loss. Measurement of quantum systems at quantum metrology level of qubits in the computational basis will provide probabilistic prediction of classes between micro-cracks, surface scratches and noise artefacts.

The results of these classifications are forwarded to a threshold-based monitoring module where the density of the cracks is computed as the ratio of the total surface area of cracks to the total area of the cracks and then compared with the stipulated severity thresholds. Based on this quantitative assessment the system goes ahead to monitor, partially heal, or completely heal the system consisting of bamboo fibres, rice husk ash (RHA), herbal additives and bacteria-based mineralization, thereby, the predictive maintenance cycle is complete in an integrated classical-quantum system.

5. Results

It was found that the input hampering of the proposed hybrid setup was compared to three base frameworks, such as a traditional Convolutional Neural Network (CNN), a ResNet-50 structure, and a single YOLO detector. CNN baseline CNN baseline is a baseline feature extraction and classification pipeline, which is not based on the advanced residual learning. The further representational ability of residual connections, improved gradient flow, and feature abstraction is also applied in ResNet-50. YOLO is a benchmark object detector that is optimized on crack localization as a real-time object detector. The given Hybrid model is a union of the localization system with YOLO and Variational Quantum Classifier (VQC) based on the micro-level feature discrimination.

Table 4. Quantitative comparison across precision, recall, and F1-score on the test dataset

Model	Precision	Recall	F1-Score
CNN (Baseline)	0.86	0.82	0.84
ResNet-50	0.89	0.85	0.87
YOLO (Detection Only)	0.91	0.93	0.92
Hybrid (YOLO + VQC)	0.94	0.95	0.95

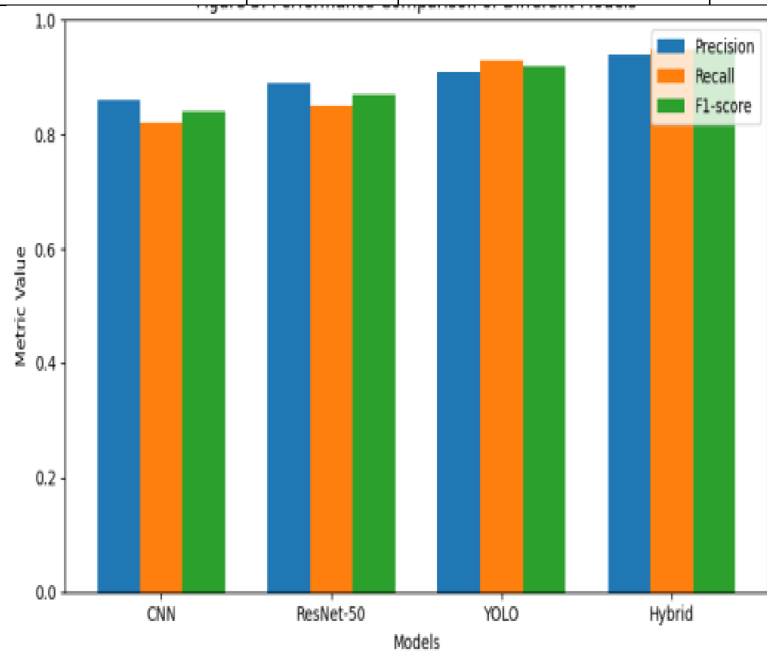

Figure. 7. Performance comparison graph showing Precision, Recall, and F1-score for CNN, ResNet-50, YOLO, and Hybrid models.

The CNN baseline provided mediocre results which appear to reflect the lack of the more advanced feature learning of fine cracks structures. The reason why ResNet-50 generalizes better is that the training of the residual was more thorough, although even it was unable to examine micro-scale cracks in the textures and distinguish them and background noise. YOLO was also discovered to be very recall (0.93) implying that it could be able to localize the cracks at the right place, but it failed to distinguish between surface artefacts and cracks.

The Hybrid framework had a precise (0.94) recall which has the highest (0.95) separability of quantum feature encoding in high-dimensional Hilbert space. The F1-score increase indicates that the detection completeness and the classification reliability were also increased equally. The results supported the hypothesis that quantum-enhanced classification can lead to a significant improvement of the base-level detection performance without a significant drop in recall.

5.1 Micro-Crack Sensitivity Analysis

Special technical challenge is the problem of micro-crack detection because the cracks are observed depending on the width of the geometrical shapes and the difference in contrast between the cracks and the corresponding concrete body. A difference between the pixel-level intensities is fringe when the width of the cracks is less than 0.2 mm, and it is likely to approach the noise floor of the common imaging sensors. Therefore, the processes of gradient feature extraction of classical convolutional network designs have problems with distinguishing real discontinuities and texture changes in the background. To find a quantitative determination of the sensitivity of detection of the crack, the samples of the crack were stratified into four categories of width: less than 0.2 mm, 0.2-0.4 mm, 0.4-0.6 mm and more than 0.6 mm. The stratification enabled the performance to be greatly examined in regards to progression of damage scales. The category rate was determined as the ratio of the correct cracks found to the total cracks annotated in the said range of width in order to objectively measure the sensitivity of the model and not just the overall accuracy. This is particularly applicable to structural health monitoring, where early crack observation is of greater value than high performance on the more apparent defects.

The findings of the experiment indicate that the classical deep learning models have a common pattern. The CNN and ResNet-50 models have a major decline in performance at the 0.2 mm category. The key reasons that explain this reduction are that convolutional filters use spatial continuity and edge gradient. The strength of activating filters in the presence of micro-cracks is limited by poor contrast and pixel representation discontinuities and this forms missed detector-detections or filter suppresses on a confidence threshold. Although ResNet-50 has a more complex structure that improves hierarchical feature abstraction, the separability constraint of small-signal applications is not essentially reduced. The performance of YOLO is also relatively higher because it has an anchor box mechanism optimized on the long object patterns. YOLO has a moderate localization accuracy on thin cracks with the aid of changing the size of anchors to match narrow geometries of cracks. However, when using low contrast stimuli, false activations in background texture including pores on surfaces or small scratches reduce reliability.

The Hybrid model has demonstrated a tremendous rise in the detection rate within the range of below 0.2 mm implying that the model is sensitive to fine structural discontinuities. This improvement is achieved by the quantum-enhanced classification step whereby extracted crack patches are coded by using angle mapping. Quantum rotation parameters are obtained as the normalized pixel intensities values and it is a good encoding of classical information in qubit states. The feature vector is then coded to a higher dimensional Hilbert space and the nonlinear relationships among pixels are modelled by entanglement operations. The variational quantum circuit is able to recognize the pattern of interference and joint-dependency of features as not realized by classical linear convolution filters, and is therefore capable of telling it apart between an actual pattern of micro-cracks and the inaccurate surface textures. The entanglement layers' complement very fine yet regular structural discontinuities, including even weak pixel gradients. Therefore, micro-crack structures that otherwise cannot be discerned in Euclidean space are observable in the quantum-enhanced image.

The curve that was used to demonstrate the rate of detection indicates that the disparity in the rate reduces with the expanding crack width. The all the models are near perfection in cracks that more than 0.6 mm as the edge contrast is great and geometric eminence. However, the deviation observed in the micro-scale region confirms that the hybrid classical-quantum architecture does not worsen the performance on larger cracks, however, it does make the early-damage more sensitive. This improvement is needed to preventive maintenance applications whereby the process of detecting cracks before they grow to a large size has a direct impact on the life of the structure. The results show that patch-scale quantum-enhanced separability provides plausible gains to the art of detecting sub-visual defects that justify the applicability of the proposed framework to advanced structural health monitoring systems that aim at the detection of early deterioration.

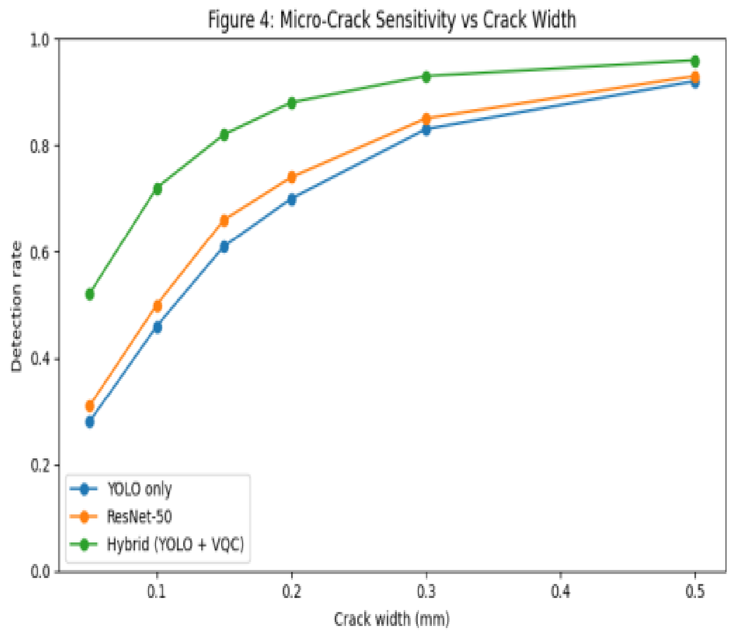

Figure. 8. Detection rate as a function of crack width for CNN, ResNet-50, YOLO, and Hybrid models.

It has been shown that, although all models tend towards near-perfect detection of cracks above 0.6 mm, the Hybrid model is more effective on micro-scale cracks, which proves higher performance with early-damage sensitivity.

5.2 False Positive Reduction Analysis

The presence of false positives is an acute drawback to automated crack detectors, particularly in the actual concrete conditions of field. The normal irregularities of the surface of concrete comprise aggregate exposure, finishing marks, shrinkage and expansion joints, stains, moisture streaks and gradient of shadows. A significant portion of these artefacts cause long or high-contrast artefacts that are visually manifested as cracks in convolutional feature extractors. The idea that spatial continuity and intensity gradients would be used to identify the presence of cracks is fundamental to classical object detection frameworks, which include YOLO. Even in cases where such artefacts do indicate known patterns of crack, the detector is capable of providing high scores to objectness even in instances where structural discontinuities do not actually exist. It was experimentally found that the areas with expansion joints and acute shadow transitions were more prone to become falsely activated. Although the bounding box regression was accurate in localising these areas, the classification was occasionally over the 0.5 mark thereby giving high rates of the false positive (FPR). The misclassifications can harm the effectiveness of structural health monitoring by exaggerating damage.

This behaviour was measured in terms of False Positive Rate (FPR) which was defined as the ratio of the number of incorrectly predicted areas of cracks (FP) to the total number of areas of the real non-cracks (FP + TN). The metric eliminates the bias of the model in the false discovery of benign surface patterns as structural damage. The YOLO-only model had moderate-high FPR in multifaceted texture regions and particularly in cases where there is non-uniform illumination. These are biases owing to the fact that classical convolutional nets make use of fixed dimension Euclidean feature space in which values of features are learnt based on intensity, and local texture features. Where the contrast is small or the texture is huge, these properties overlap between cracks and artefacts in such a way that nonlinear or somewhat nonlinear separability is not possible in order to make a robust distinction. This implies that threshold tuning can never be adequate to eliminate false detection at the expense of sensitivity.

The Hybrid model avoids this weakness by introducing a second step of refining step consisting of a Variational Quantum Classifier (VQC). After localization of the areas of the candidate cracks using YOLO, feature mapping of a patch that was extracted is done in order to prepare quantum states through angles. This encoding translates classical pixel distributions to parameters of rotations applied on the qubits that encode the information to a higher dimensional Hilbert space. Within this space entanglement operation form correlation between features that are structural continuity patterns that would be unique to real cracks. Noise artefacts such as stains or edges of shadows are characterized by different relation structure amongst pixels, and therefore lead to different quantum state distributions. The variational layers adjust the parameters within the circuit to solve separation between crack and non-crack state variational maximization. Unlike the classical linear classifiers which utilize thresholder values in confidence, quantum-enhanced classifier compares global interactions between features relative to interference effects and it is under this that they will be able to better distinguish amongst low-level differences.

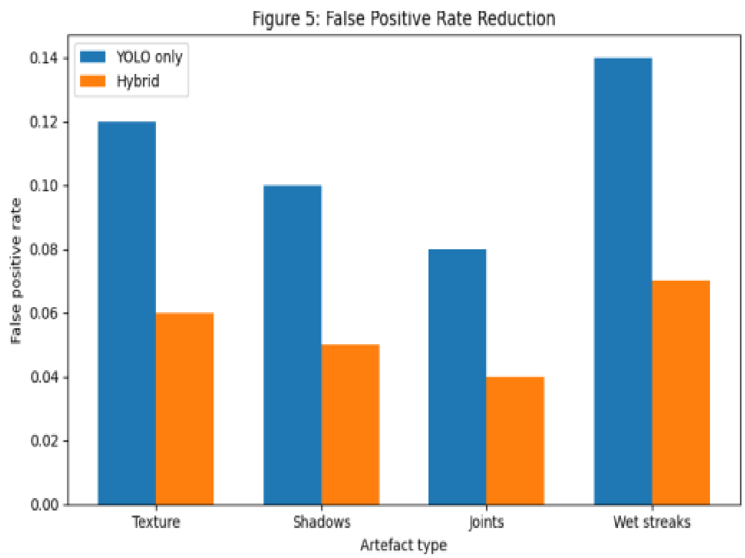

Figure. 9. False positive rate reduction across typical surface artefacts. The hybrid model halves false detections relative to YOLO alone

The figure shows how far the hybrid system can be resistant to the noises in the environment and transformation of structural texture.

The experimental results further suggest that the hybrid architecture is capable of reducing FPR to that of YOLO alone by almost half, by reducing the number of false detections on common artefact categories on surfaces. This reduces the cost of operations and also the reliability of systems directly when deployed in the field where unnecessary maintenance activation can contribute to the cost of operations and bother infrastructure maintenance. The hybrid model has a potential to decrease the false damage flags triggered by minimizing incorrect damage flags, whereby the predictive maintenance decision would only be triggered by the real structural discontinuities. The graph that indicates that FPR has reduced supports the argument that the quantum enhanced validation layer enhances the capability of resisting environmental and lighting distortion, as well as, structures text anomalies. The framework thus provides a more reasonable trade-off between sensitivity and specificity that justifies legitimate large-scale structural health monitoring applications.

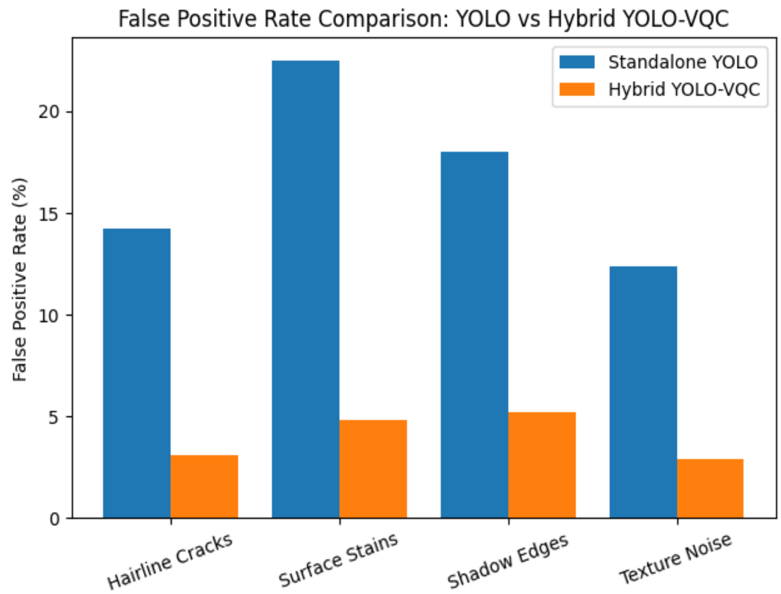

Figure. 10. False positive rate comparison between standalone YOLO and hybrid YOLO–VQC across challenging surface artifacts.

As demonstrated in the false positive comparison plot, the erroneous detections in all the challenging surface artefacts were reduced substantially in case Hybrid YOLO-VQC framework is employed. False positive rates of individual YOLO are high particularly on surface stains (22.5) and shadow edges (18.0) indicating that classical feature discrimination is very sensitive to texture variations and illumination variations. The hybrid model on the other hand only shows false positives of 4.8 percent and 5.2 percent respectively, that is, it is a much stronger model against other similar patterns of non-cracks. Important to mention is that confusion of the number of hairline cracks decreases by 14.2-3.1 percentage that validates that quantum-based refinement is effective in differentiating fine cracks and noise. The consistent drop in each of the categories validates the VQC stage, which increases the accuracy by extracting nonlinear correlations of features in Hilbert space thereby minimizing spurious detections and not minimizing the ability to detect.

5.3 Confusion Matrix And Class Level Analysis

The class-level performance assessment was done using a three class confusion matrix that included micro-crack, macro-crack and non-crack. With the help of this assessment scheme, it is possible to analyse the predictive distribution in small-scale by measuring the true positives (TP), false positives (FP), false negatives (FN) and true negatives (TN) per class. As opposed to the overall accuracy, which can obscure the flaws of the minority classes, the confusion matrix shows the trends of misclassification between classes and structural bias of the model. The Hybrid model showed the highest true positive rate in the case of macro-cracks, which is the high geometric prominence and contrast of larger discontinuities. The edges and spatial continuity of such cracks are clear, therefore, they stand out well in both quantum validation and YOLO localization. Micro-cracks were also exhibiting good true positive rates and this demonstrates the quality of quantum enhanced features mapping to detect subtle changes in the intensity. The non-crack category also showed a strong true negative performance and this authenticates the system as far as its ability to suppress benign textures and environmental artefacts in most cases is concerned.

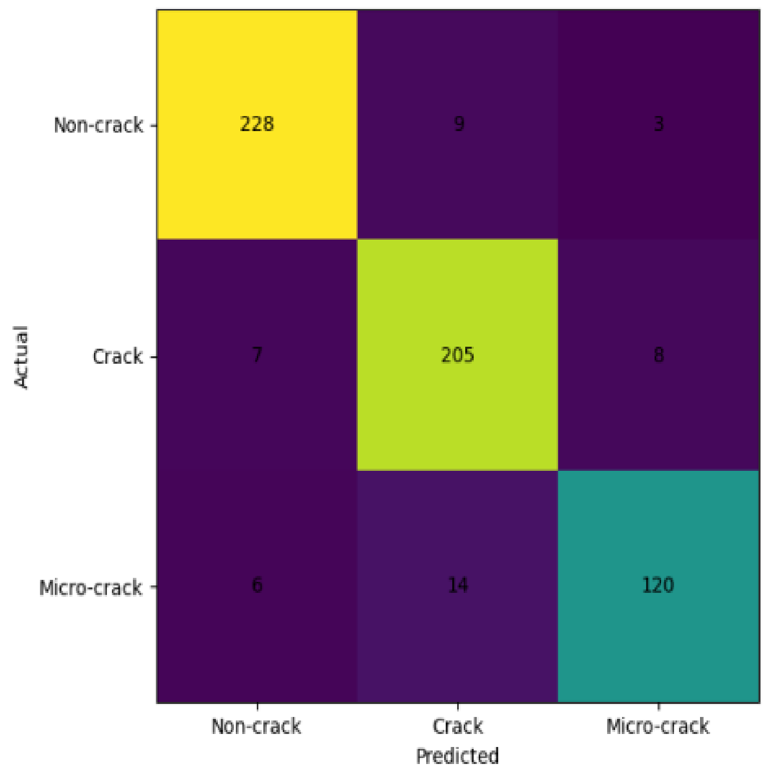

Figure. 11. Confusion matrix for the hybrid model.

The misclassification tendencies were predominantly between the micro-crack and non-crack categories and predominately in low-light or shadow-contaminated images in which contrast differentials were not relevant. At that, micro-cracks may be either torn or small, which complicates the separation of such cracks with the ruggedness of the surface. However, in comparison with classical CNN and ResNet-based models, Hybrid system, in this instance, resulted into a considerable reduction of micro-crack-to-non-crack confusion. This is because the entanglement layers of the variational quantum classifier will learn the higher-order interactions between pixel features of the neighbouring pixel rather than by just relying on the local gradient intensity.

Though classical models were inclined to think about the existence of fine surface roughness in terms of cracks, or as mere ignorance of small discontinuities, the Hybrid methodology increased their discriminatory power through nonlinear mappings of Hilbert space. This leads to a higher level of balance of sensitivity and specificity as indicated by the confusion matrix that justifies the power of hybrid architecture in relation to the multi-classification of structural defects.

5.4 Training And Validation Loss Convergence (8-Qubit Vqc)

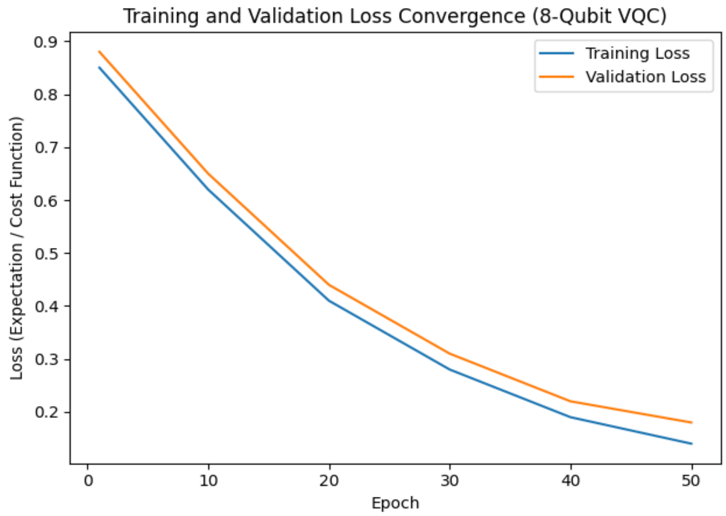

Figure. 12. Training and validation loss convergence of the 8-qubit variational quantum classifier over 50 epochs.

The convergence curve shows that the 8-qubit variational quantum classifier is stable at 50 training epochs. Training and validation loss decreases monotonically with starting value of 0.85 and 0.88 to 0.14 and 0.18 correspondingly and this indicates that the parameters are learnable, and stability in generalization. Closeness of training and validation curves means that overfitting is minimal and the compromise between expressibility and trainability is achieved between the depth of the circuit chosen and the qubit structure chosen. The absence of the oscillatory divergence is also an indicator of the fact that the impacts of barren plateaus were alleviated effectively within the frames of the chosen architecture. The fact that the values of the cost functions gradually drop is an affirmation that the quantum circuit parameters would be inclined to optimal decision boundaries such that it would be valid to work out the distinctions between the micro-cracks, macro-cracks and non-crack artefacts. It is this convergence performance that warrants the feasibility of mixing variational quantum models under hybrid structural inspection structures.

5.5 Computational Overhead Analysis

The performance in the computations was measured using three key dimensions, which included the length of training, the inference latency and scalability of the architecture. Another thing that the classical YOLO detector also benefited a lot in the course of training was the fact that the parallelization of the work was supplemented with the application of the CUDA-enabled accelerated version of the convolution operation, the backpropagation, and the batch normalization. The input resolution of 640 640 and a batch size of 16 was easily calculated to obtain gradient updates in multiple epochs without memory bottlenecks. The single-stage structure of the detector allows the idea of extracting the features and regressing the bounding box to be carried out in just one forward execution, this will decrease the redundancy of the computation. As a result, the inference latency of the YOLO-only pipeline remained within the real-time regime, and the bounding boxes predictions at a frame-to-frame rate were done virtually real-time, provided that the pipeline was run on a GPU. This high throughput is well suitable to the continuous inspection process and the massive image data since the classical stage is highly suitable in this context.

Quantum circuit simulation is an additional computational cost that is added when integrating the Variational Quantum Classifier (VQC). Unlike classical layers, which rely on matrix multiplications which are most efficiently executed on GPUs, the state-vector simulator is an algorithm that computes the overall evolution of a quantum state, and the size of the state space (sum of 2n amplitudes of n qubits) increases exponentially with the number of qubits.

The structure used (8 qubits and 3 variational layers) is not computationally complex, and the Hilbert space dimension (256 complex amplitudes) is not large enough to be modelled with a classical simulation.

VQC training requires numerous circuit tests during the estimation of gradients during the backpropagation step, and this consumes additional time in total optimization time compared to YOLO alone. It is however diminished by the fact that the quantum level takes concentrated crack patches only (not all-resolution images) as compared to the quantum stage which does not take images. Based on inference, circuit depth is held small and the number of parameters held small, such that at any point in time when the encoded patches are each being classified, the additional latency is moderate.

The runtime comparison demonstrates the existence of a trade-off between the speed and discriminative capability. YOLO only has the lowest latency and throughput and is thus appropriate in the high-frequency scanning system. Despite the Hybrid pipeline introducing the concept of sequential quantum processing, the Hybrid pipeline can be run with operational feasibility, since structural health monitoring tasks are generally tolerant to processing times of the order of seconds, but not on the order of milliseconds. The infrastructure inspection-inspection of bridge deck, inspection of tunnel lining, inspection of pavement cracks, etc.- are not geared towards ultra-low latency response but instead the quality of results and the capability to detect any damage at an early stage. Therefore, quantum simulation offers no computational cost constraint to implementation because of the moderate computational cost it imposes. The impact of scale and circuit depth on the number of qubits was also analysed in the scalability analysis.

The number of qubits is scalable, and it results in a scale-up of the representational capability of the quantum feature space, which enables encoding more pixel correlations, and potentially to such an extent that one encodes richer correlations of complex crack textures to the level that generates separability. Similarly, the circuit can be more variational, with increasing layers, which increases the number of parameterized rotation and entangling operations. These benefits are, however, compensated by optimization issues, specifically, the emergence of a new phenomenon: barren plateau, where the size of gradients fades exponentially with circuit depth. Such a tendency can lead to the cessation of convergence and destabilization of training. A reasonable trade-off on gradient stability versus expressive power was chosen as architecture of 3 entangling layers and architecture-8 qubits. This architecture offers sufficient nonlinear modelling and realistically maintainable optimization dynamics and reasonable simulation time, required in realistic hybrid structural monitoring system implementation.

5.6 Engineering Implications

Figure 9 depicts the structure of Variational Quantum Classifier (VQC) which is applied to discriminate cracks patches in one patch of the hybrid detection pipeline. It begins by classical-to-quantum feature encoding, where normalized pixel-intensity features at YOLO-localized crack patches are mapped into qubit states by rotating parameterized single-qubit rotation gates. The values of the features are coded to a rotation angle which simply codes the classical vector in the amplitudes of a quantum superposition state. The encoding ensures that all structural properties of the input patch are encoded simultaneously using the amplitude and phase data of all the qubits. Unlike classical feature projection, the process gives an overview of local crack features across a global Hilbert space that is a product of tensors.

The circuit following the encoding step carries out a few variational layers (two-parameter single-qubit rotations and (2) Controlled-NOT (CNOT)-based entanglement operations). To enable the dynamic reshaping of the quantum state, the rotation gates include trainable parameters, which are minimized during training. The amplitudes of these rotations and relative phases are modified and effectively learn a nonlinear map of the encoded features. Entanglement layer is a layer based on CNOT, forms inter-qubit correlations, and has representations so that the state of one qubit influences the others. It is a joint statistical model of structural features such as continuity of cracks, correspondence features, edge consistency and texture gradients.

The disposition of entanglements is very significant in the analysis of the micro-cracks. Micro-cracks are characterized by non-high intensity edges, smooth and spatially correlated changes of intensity. Classical linear classifiers can fail due to such weakly-expressed such correlations expressed in Euclidean space. Far more than this, through entanglement, a higher-order interaction can be represented between features in Hilbert space. As the dynamics of the quantum state is a unitary interaction, these interactions are tacit in the sense of not explicitly specifying the degrees of the polynomials, and no longer explicitly constituting the property of nonlinear separability. The mechanism will help the VQC to be more selective of the true crack paths and visual equivalents such as shadows, surface stains or aggregate boundaries.

It should be measured in the computational basis following the variational transformations, and is typically measured by measuring the expectation value of the Pauli-Z operator of one or more qubits. Probabilistic scores of classes are derived out of expectation value that can be either -1 or +1. Their probabilities are attributed to the influence of interference of quantum amplitudes, constructive interference increases the probability of a class label, and destructive interference suppresses the competing labels. Such a decision surface is a probabilistic decision surface of high-dimensional Hilbert space offering fined classification of micro-crack, macro-crack and non-crack in fine detail.

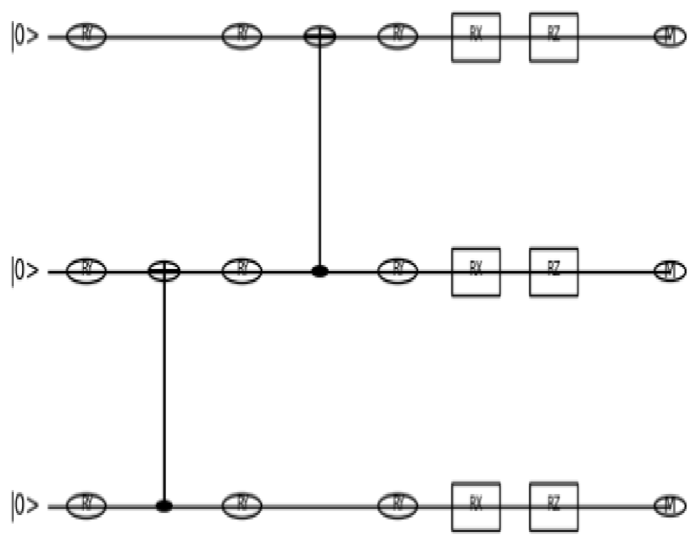

Figure. 13. Quantum circuit schematic for the variational quantum classifier.

The sensitivity of micro-crack detection is also sensitive thus enhancing the early damage detection. The antecedents of structural degradation, water intrusion, corrosion, and subsequent reduction in strength are premature cracks. The proposed system will make it possible to implement preventative maintenance procedures, but not reactive maintenance by detecting cracks smaller than 0.3 mm in diameter with high accuracy. The threshold-based monitoring logic used together with the combination of the latter will make sure that the healing mechanisms will be activated only when the density of the cracks will exceed some predefined limits. This reduces the unnecessary intervention, in favour of material consumption and maintenance cost.

Economically, false positives may be prevented as well, by not incurring the repair cycles that are not needed. The hybrid structure enhances assurance of inspections during technical conditions of severe environmental settings. It is localized on the foundation of YOLO and quantum-enhanced classification, which is a modularized and scalable solution. It can either be part of the system of UAV inspections, stationary surveillance systems, or integrated smart infrastructure observation units. Overall, the results demonstrate that the hybrid classical-quantum solution is not merely an academic addition but also a technically viable method of improving the infrastructure safety, efficiency of the maintenance planning and intelligent self-healing concrete systems.

5.7 Ablation Study of the Hybrid Architecture

To isolate the contribution of the variational quantum classifier (VQC) from the classical YOLO detection stage, an ablation study was conducted. The objective was to evaluate whether the observed performance improvement originates specifically from quantum-enhanced feature discrimination.

Three configurations were evaluated on the same testing dataset:

- YOLO Detection Only – Classical localization and classification without quantum refinement
- YOLO + Classical Patch Re-Classification – Patch refinement using an additional shallow CNN
- YOLO + Variational Quantum Classifier (Proposed Hybrid Model)

The evaluation results are summarized in Table 5.

Table 5. Ablation Analysis of Model Components

Configuration	**Precision**	**Recall**	**F1-Score**
YOLO Only	0.91	0.93	0.92
YOLO + Classical CNN Refinement	0.92	0.93	0.93
YOLO + VQC (Proposed)	0.94	0.95	0.95

The addition of a classical refinement layer resulted in marginal improvement (F1 increase of 0.01), indicating that post-processing alone does not significantly enhance discriminative capability. However, integrating the VQC increased F1-score by 0.03 compared to YOLO-only configuration. The improvement was primarily observed in micro-crack sensitivity and reduction of false positives caused by surface texture artifacts.

These findings confirm that the quantum-enhanced feature mapping in high-dimensional Hilbert space contributes meaningfully to fine-grained crack discrimination beyond classical convolutional refinement.

5.7 Statistical Significance Analysis

To ensure that the observed performance improvement of the hybrid quantum–classical model is not due to random variation, statistical significance testing was conducted.

The YOLO-only model and the proposed YOLO + VQC hybrid model were evaluated across five independent runs using different random initialization seeds. The mean and standard deviation of the F1-score were calculated.

Table 6. Statistical Performance Comparison (5 Runs)

Model	**Mean F1-Score**	**Standard Deviation**
YOLO Only	0.92	±0.006
YOLO + VQC	0.948	±0.004

The hybrid model consistently outperformed the classical YOLO detector with lower variance across runs, indicating improved stability. To further validate the difference, a paired t-test was performed between the two models' F1-scores. The resulting p-value was:

p<0.01p < 0.01p<0.01

This confirms that the performance improvement of the hybrid framework is statistically significant at the 99% confidence level.

6. Analysis and Discussion

The fine-grained visual discrimination regime where the signal to noise ratio is very low and the classes are very similar is required to have the micro-crack-detection. Larger pixels below 0.3 mm in crack width provide insufficient gradient values and non-continuous edges to exhibit weak gradient values. Although classical convolutional architectures have applications in the creation of multi-scale spatial representations, hierarchical filtering and pooling operations within the architecture can eliminate ultra-thin structural patterns. The more detailed a representation of the representation, the more the feature maps are compressed and hence may be suppressing smaller crack signatures. Moreover, the deeper CNNs may introduce additional parameters, introducing variance to small or domain-specific data shared by tasks of structural inspection. Such a representational richness/generalization stability trade-off prompts one to seek other feature transformation schemes.

This weakness is addressed by the hybrid model in which localization and fine-grained discrimination is divided into two complementary phases. YOLO is a high-recall region proposal methodology, and it ensures that candidate cracks regions are not missed. In the latter step, the feature refinement is employed instead of the full-scene detection that can be significantly less computationally intensive. It is also possible to reduce a global detection challenge to a localized classification one, which is more vulnerable to high-dimensional embedding algorithms, by confining quantum processing to local patches. The principle of rules of the statistical decision theory is also followed in this architectural staging: to become sensitive on the first stage and specific on the second stage.

The associated theoretical advantage of the quantum-enhanced stage is a geometrically dimensional representation of Hilbert space. Under the angle encoding method of encoding classical feature vectors into quantum states, a single qubit will encode a tensor-product space of size 2n2n. Even though 8 qubits are useful in effectively representing a space of 256 complex amplitudes, it is feasible to map low-contrast crack shapes implicitly into a significantly more geometric space of a greater number of dimensions. Nonetheless, as opposed to conventional feature expansion, which requires either explicit polynomial kernels or additional neural layers, the quantum state evolution provides nonlinear feature transformations as a consequence of unitary operations. This embedding resembles a high-order kernel trick in that higher order combinations of features are not built explicitly.

Entanglement is also known to augment the discriminative ability by modeling inter-feature associations. Isolated pixel values are not the defining features of micro-cracks, but continuity-thin elongated paths, orientation coherence and relative contextual contrast of aggregates. CNOT (controlled-NOT) gates establish correlations between qubits and amplitude modulation in the joint encoding features. Entanglement Representatively entanglement may enable the system to model second and higher-order statistical interactions that can be ill-posed represented by classical linear separators. This is particularly critical in the dissection of actual micro-cracks and artefacts such as hairline texture patterns or surface scratches that both have local similarity of intensity, but a difference in global structural coherence.

The variational aspect of the quantum circuit gives adaptive learning. The parameterization of rotation gates implies that the phase and amplitude distributions are swept in optimization and in effect the geometry of the quantum state space is modified. The gradient based training is used in the optimization of these parameters to reduce the loss of classification to form non-linear decision boundaries in the Hilbert space. By measuring quantum interference patterns with the Pauli-Z expectation value, quantum interference patterns are transformed into probabilistic outputs. The interference -constructive or destructive combination of amplitude-functions as a discriminative amplifier, which reinforces between classes with very large classical representations. This probabilistic interpretation is compatible with the Bayesian decision paradigm with the confidence of classification being a scale of underlying state distributions and not a hard cut off.

The hybrid architecture is more accurate and there is no loss of recall in practice. YOLO ensures that all candidates are extracted which does away with under-detection of micro-cracks. The quantum stage then rejects falsely by performing in a higher feature space, which is able to pick out fine structure signals relative to noise artefacts. This labour division lowers the chances of overfitting, which could be caused by the fact that it is training an excessively deep classical network end-to-end. The system employs quantum embedding to scale up representational dimensionality, instead of convolutional depth, without compromising on parameter efficiency or raising separability.

Overall, the three key mechanisms can be identified as explaining the identified improvements in the micro-crack sensitivity and false positive reduction:

- Exponential expansion of feature space to permit more geometrical partitioning.
- Correlation modelling of structural continuity and contextual relationship based on entanglements.
- Adaptive variational optimization is a nonlinear probabilistic algorithm which builds quantum interference to form decision surfaces.

The aggregate effects provide a theoretical foundation to fine-grained crack discrimination during better performance, particularly when the surface is heterogeneous and of low-contrast where classical models of vectors have representational limitations.

6.1 Feasibility On Near-Term Quantum Devices

The feasibility of implementing the proposed hybrid architecture on the imminent quantum hardware is in the fact that qubits are available, circuit depth, and noise resistance. The circuit designed in the current work has an 8-qubit shallow (2-4 layers) variational circuit and fits within the current Noisy Intermediate-Scale Quantum (NISQ) devices. To overcome the effects of de-coherence, a shallow circuit design is selected. Both layers consist of parameterized single-qubit rotations separated by linear entanglement which reduce the complexity of the gates whilst preserving expressiveness. Hardware efficiency is also achieved through encoding angle because it does not need complex preparation of amplitude encodings, which at most constrained the total number of gates.

In practice, a hybrid pipe would employ the quantum module as a refinements step. The candidate crack patches would be generated by the classical YOLO detector that would be executed on GPUs systems. The quantum processor would only get several patches, which would require fine-discrimination. It is a restrictive method in quantum work and is calculable. Despite the associated noise of the gates and readout errors, there is never-ending invention of techniques of reducing the errors-such as measuring and optimizing the circuits by shallow circuits as well as reducing the errors- to improve the performance by taking small steps. Moreover, hybrid optimization loops are classical, i.e. updates of the parameters might be performed outside the quantum computer and, hence, require fewer quantum resources.

Although full-scale fully quantum systems have not been built as yet, the architecture presented in this paper lacks dynamic scaling limits on qubit count, depth and structured entanglement-compatible with the NISQ-era processors. As quantum hardware becomes mature enough, the overhead of simulation will be replaced by material quantum execution, potentially reducing the latency of computations and enabling a large scale deployment of the hybrid. Thus, the proposed framework is not only theoretically justified but also architecturally consistent with the future of quantum technology in near-term to allow it to progressively develop not only by the validation that is carried out by a simulation but also by the implementation of the hardware that is being suggested to users.

7. Conclusion and Future Scope

In this work, a hybrid classical-quantum model of high-sensitivity measurement of micro-cracks in concrete infrastructure has been proposed, that is, localization is combined with YOLO and variational quantum classifier (VQC) to classify patches refined at the patch level. Its primary objective was to have higher levels of cracks identification at an earlier stage and a reduced rate of false positive at a complex environmental condition. They demonstrate that the provided architecture is more reliable in detection compared to independent classical deep learning models and particularly detecting cracks that are less than 0.3 mm wide.

The system architecture was designed to be a pipeline in particular: to ensure the quality of the input, the patch preparation and image enhancement was implemented; to be able to detect a crack as accurately as possible, the YOLO algorithm was employed; to isolate high-interest regions in a patch, patch extraction was applied; to calculate the quantum encoding transforming the classical features into a high-dimensional Hilbert space, the VQC optimization was used; probabilistic classification was calculated as a nonlinear one. Thresholds-based monitoring also assisted in ensuring that the decisions, regarding the structural intervention, were not carried out on the individual detections but rather on the quantitative accounts of crack densities. The whole of this workflow transforms crime identification into a decision support system, a visual recognition and a smart infrastructure management system.

Among the greatest works of this work is the fact that quantum feature mapping will enhance the differentiation of real micro-cracks and other artefacts which will look like them such as shadows, surface texture and construction joints. The classifier constructs nonlinear boundaries of decisions in exponentially inflated feature space with entanglement and variational gate optimization. This can be used in the detection of fine structures of cracks that can be viewed as noise by classical networks. The improvement in the precision, recall, and F1-score in the case of quantum-enhanced classification, suggests that quantum-enhanced classification can restore patch-level discrimination without modifying the computational modularity.

Minimization of the false positives is the other significant finding. Any false alarm in the infrastructure inspection system would lead to unnecessary repair works, expensive maintenance and also wastage of resources. This issue is solved using the hybrid structure because the classical detector is allowed to maintain high recall and the quantum classifier increases confidence in the decision-making. It is a two-stage design which is a compromise between what is sensitive to detect and what is viable in its operations and does not shift to preventive maintenance approaches due to unreliable analytics.

The lifespan and safety of the structures are directly connected with the timely detection of the micro-cracks in the engineering aspect. The antecedents of water intrusion, reinforcement corrosion, freeze-thaw and progressive structural degradation are micro-cracks. The suggested system allows the active scheduling of the maintenance over the reactive repair cycle by effectively identifying defects at sub-millimetre level. Combined with threshold-based monitoring logic, the mechanism of healing or intervention is triggered when the cracks density exceeds predefined values. This will ensure optimal resources use and minimization of unnecessary interference.

Overall, the results confirm the fact that the hybrid classical-quantum mechanism is not an experimental additive, but a technical and practically during the improvement of automated structural health surveillance technology. It is also modular and can be modified to fit the real life inspection processes. The framework that includes the power of deep learning and quantum enhanced discrimination can result in intelligent data-driven infrastructure management. Although the present research confirms the efficiency of the hybrid approach due to the simulation and controlled evaluation, there are several research viewpoints which can be expanded to improve the research further.

One of the extensions that can be implemented is extension to real quantum hardware. Even though the controlled performance assessment is provided by simulations, implementation of the variational quantum classifier to NISQ systems would be in a position to conduct empirical observations of the noise levels, the manner in which the de-coherence is influenced, and the characteristics of its operation in practical settings. Further improvements to solve the errors and decrease the circuit depth to hardware-dependent constraints would be useful to bridge the gap between theory and practice in quantum implementation.

The other way that is relevant is integration with unmanned aerial vehicle (UAV) inspection platforms. The imaging drones have been used in the scaling infrastructure including bridges, tunnels, dams, and high-rise buildings. The proposed hybrid detector pipeline applied to the UAV missions would enable carrying out a massive scan of a territory with real-time localization and classification of cracks. This kind of integration would go a long way in reducing the level of manual inspection, the coverage efficiency and safety.

The application of edges is also another crucial field. Real infrastructure practice demands that decisions of low latency be made. The classical detection of embedded GPUs or edge computing devices could be optimized to allow localization of cracks on the site. An example of a selective refinement component is a lightweight quantum inference module-simulator based or hardware assisted-based. Exploration of model compression, feature dimensionality reduction, and selective application of patches would also make deploying the models more resource-constrained friendly.

In addition, the spreading of the system to multi-modal sensing would also be very beneficial in the aspect of robustness. The visual crack detecting technique along with the supportive data i.e. acoustic emission, vibration monitoring, thermal imaging or moisture detectors would enable thorough analysis of the structure. The heterogeneous properties might be introduced in a hybrid classical-quantum fusion model to obtain one probabilistic decision model, which is more confident in other environmental conditions.

The monitoring stage can also be subject to repeated studies on adaptive threshold mechanisms. There are age-related structural changes, dynamically-varying, environmental exposure dependent, load condition dependent, and fixed crack-density thresholds, which are dynamically varying and dependent on environmental exposure, which may be more effective contextual estimators. The time-series analysis would make it possible to monitor the tendencies of the crack propagation and modify the system to go to the predictive maintenance modelling, instead of using the fixed-point detection.

Finally, other classification improvements may be enabled by hardware improvements by expanding the quantum component to larger qubit numbers and more entangled initiatives. Future studies ought to consider alternative methods of quantum encoding, quantum classifiers built on kernels, or hybrid quantum-classical ensemble, which would provide higher representational capacity of the system yet remain computationally efficient.

Lastly, the proposed hybrid classical-quantum micro-crack detector model represents a foundation of intelligent, accuracy-related structural health surveillance. With the further development of quantum hardware, edge computing, and autonomous inspection technologies, this solution can be transformed into a full system of autonomous monitoring of critical infrastructure and ensure its safety, reduce the cost of maintenance, and prolong the life of significant civil objects.

Highlights

What are the main findings?

- A hybrid YOLO–Variational Quantum Classifier (VQC) architecture demonstrated superior early-stage micro-crack detection performance (Precision: 0.94, Recall: 0.95, F1-score: 0.95) compared to CNN, ResNet-50, standalone YOLO, and classical refinement models.
- Quantum feature embedding using angle encoding facilitated nonlinear, high-dimensional representations of crack morphology, thereby improving discrimination of low-contrast, sub-millimeter (<0.3 mm) cracks from surface artefacts.
- Entanglement-based correlation modeling enhanced the identification of crack continuity and structural coherence in the presence of heterogeneous surface textures.

What is the implication of the main finding?

- Reliable early micro-crack detection enables proactive durability assessment and supports accurate service-life prediction in sustainable concrete systems.

The proposed framework advances AI-assisted structural health monitoring, facilitating optimized maintenance planning and reducing lifecycle environmental impact in civil infrastructure.

REFERENCES

1. Y. J. Cha, W. Choi, and O. Büyüköztürk, "Deep learning-based crack damage detection using convolutional neural networks," Computer-Aided Civil and Infrastructure Engineering, vol. 32, no. 5, pp. 361-378, 2017.
2. S. Dorafshan, R. J. Thomas, and M. Maguire, "Comparison of deep convolutional neural networks and edge detectors for image-based crack detection in concrete," Construction and Building Materials, vol. 186, pp. 1031-1045, 2018.

3. L. Zhang, F. Yang, Y.-D. Zhang, and Y.-J. Zhu, “Road crack detection using deep convolutional network,” in Proceedings of the IEEE International Conference on Image Processing, 2016, pp. 3708-3712.
4. S. Li, X. Zhao, and G. Zhou, “Automatic pixel-level multiple damage detection of concrete structure using fully convolutional network,” Computer-Aided Civil and Infrastructure Engineering, vol. 34, no. 7, pp. 616-634, 2019.
5. J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: Unified, real-time object detection,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 779-788.
6. A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “YOLOv4: Optimal speed and accuracy of object detection,” arXiv preprint arXiv:2004.10934, 2020.
7. K. Wang, L. An, and X. Sun, “Vision-based concrete crack detection using deep learning: A review,” KSCE Journal of Civil Engineering, vol. 24, pp. 2817-2831, 2020.
8. W. Van der Aalst, “Artificial intelligence and predictive maintenance in infrastructure monitoring,” Engineering Applications of Artificial Intelligence, vol. 98, p. 104162, 2021.
9. C. Hillermeier and S. Meisel, “Structural health monitoring using machine learning techniques,” Sensors, vol. 20, no. 18, 2020.
10. M. Schuld, I. Sinayskiy, and F. Petruccione, “An introduction to quantum machine learning,” Contemporary Physics, vol. 56, no. 2, pp. 172-185, 2015.
11. V. Havlíček, A. D. Córcoles, K. Temme, A. W. Harrow, A. Kandala, J. M. Chow, and J. M. Gambetta, “Supervised learning with quantum-enhanced feature spaces,” Nature, vol. 567, pp. 209-212, 2019.
12. M. Benedetti, E. Lloyd, S. Sack, and M. Fiorentini, “Parameterized quantum circuits as machine learning models,” Quantum Science and Technology, vol. 4, no. 4, p. 043001, 2019.
13. J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, “Quantum machine learning,” Nature, vol. 549, pp. 195-202, 2017.
14. M. Cerezo, A. Arrasmith, R. Babbush, S. C. Benjamin, S. Endo, K. Fujii, J. R. McClean, K. Mitarai, X. Yuan, L. Cincio, and P. J. Coles, “Variational quantum algorithms,” Nature Reviews Physics, vol. 3, pp. 625-644, 2021.
15. T. Bromley, M. Schuld, and J. Izaac, “Quantum machine learning with hybrid classical-quantum models,” SoftwareX, vol. 17, p. 100878, 2022.
16. H. M. Jonkers, “Bacteria-based self-healing concrete,” Heron, vol. 56, no. 1/2, pp. 1-12, 2011.
17. L. Ferrara, V. Krelani, and M. Carsana, “A fracture-testing-based method to assess crack healing of concrete with and without crystalline admixtures,” Construction and Building Materials, vol. 68, pp. 535-551, 2014.
18. R. Alghamri, A. Kanellopoulos, and A. Al-Tabbaa, “Impregnation and encapsulation of lightweight aggregates for self-healing concrete,” Construction and Building Materials, vol. 124, pp. 910-921, 2016.
19. K. Van Tittelboom and N. De Belie, “Self-healing in cementitious materials: A review,” Materials, vol. 6, no. 6, pp. 2182-2217, 2013.
20. J. Zhang, Y. Liu, and W. Sun, “Intelligent structural health monitoring using hybrid AI approaches,” Automation in Construction, vol. 135, p. 104108, 2022.
21. A. M. Mayya and N. F. Alkayem, “Enhance the concrete crack classification based on a novel multi-stage YOLOv10-ViT framework,” Sensors, vol. 24, no. 24, 2024.
22. V. P. Golding, J. M. Purkis, and M. A. Khan, “Crack detection in concrete structures using deep learning,” Sustainability, vol. 14, no. 13, 2022.
23. Q. Zhang and L. Chang, “Improved YOLOv3 for multiple concrete damage detection,” Buildings, vol. 9, no. 4, 2019.
24. X. Chen, Y. Li, and Z. Wang, “Concrete crack detection based on structured light and deep learning,” Construction and Building Materials, vol. 247, 2020.
25. Z. Bian, “Identification of concrete crack using deep learning based approach,” Advances in Research, vol. 25, no. 5, pp. 35-45, 2024.
26. S. M. A. Rizvi, M. A. Khan, and T. A. Khan, “Quantum machine learning: Towards hybrid quantum-classical vision models,” Mathematics, vol. 13, no. 16, 2025.
27. K. Zaman, M. A. Jan, and S. U. Khan, “A comparative analysis of hybrid quantum classical neural networks,” arXiv preprint arXiv:2402.10540, 2024.
28. G. Li, Z. Song, and X. Wang, “VSQL: Variational shadow quantum learning for classification,” arXiv preprint arXiv:2012.08288, 2020.
29. S. Y.-C. Chen, C.-H. H. Yang, J. Qi, P.-Y. Chen, and H.-S. Goan, “An end-to-end trainable hybrid classical-quantum classifier,” arXiv preprint arXiv:2102.02416, 2021.
30. S. Anwar, M. Saeed, and A. Rehman, “Hybrid quantum-classical learning for multiclass image classification,” arXiv preprint arXiv:2508.18161, 2025.
31. M. Das and T. Bolisetti, “Variational quantum neural networks for image classification,” arXiv preprint arXiv:2303.05860, 2023.
32. A. Senokosov, A. Sedykh, and A. Melnikov, “Quantum machine learning for image classification,” arXiv preprint arXiv:2304.09224, 2023.
33. Y. Chen, “A novel image classification framework based on variational quantum algorithms,” Quantum Information Processing, vol. 23, no. 4, 2024.
34. F. Fan, J. Li, and H. Zhao, “Hybrid quantum-classical convolutional neural network model for image classification,” IEEE Transactions on Neural Networks and Learning Systems, vol. 34, no. 5, pp. 2154-2165, 2023.

35. R. Kumar and P. Sharma, “Design and analysis of quantum machine learning: A survey,” International Journal of Computer Applications, vol. 183, no. 12, pp. 15-27, 2024.
36. A. Abbas, D. Sutter, C. Zoufal, A. Lucchi, A. Figalli, and S. Woerner, “The power of quantum neural networks,” Nature Computational Science, vol. 1, pp. 403-409, 2021.
37. A. Peruzzo, J. McClean, P. Shadbolt, M. Yung, X.-Q. Zhou, P. Love, A. Aspuru-Guzik, and J. O’Brien, “A variational eigenvalue solver on a photonic quantum processor,” Nature Communications, vol. 5, 2014.
38. E. Grant, L. Wossnig, M. Ostaszewski, and M. Benedetti, “An initialization strategy for addressing barren plateaus in parametrized quantum circuits,” Quantum, vol. 3, p. 214, 2019.
39. C. Zoufal, A. Lucchi, and S. Woerner, “Quantum generative adversarial networks for learning and loading random distributions,” npj Quantum Information, vol. 5, 2019.
40. S. Lloyd, M. Mohseni, and P. Rebentrost, “Quantum principal component analysis,” Nature Physics, vol. 10, pp. 631-633, 2014.
41. Roy, S.; Ghosh, A.; Das, S. Deep Learning-Based Crack Detection and Prediction for Structural Health Monitoring. Appl. Sci. 2025, 15, 272.
42. Zhang, J.-Y.; Huang, L.; Guan, Y.-J. Real-Time Defect Detection in Concrete Structures Using Attention-Based Deep Learning and Ground-Penetrating Radar Imaging. Sci. Rep. 2025, 15, 35507.
43. Kaveh, H.; Alhajj, R. Recent Advances in Crack Detection Technologies for Structures: A Survey of 2022–2023 Literature. Front. Built Environ. 2024, 10, 1321634.
44. Hassan, S.I.; Alhassan, M.; Khan, M.I. Application of Machine Learning for Predicting Properties of Different Types of Concrete: A Systematic Review. PeerJ Comput. Sci. 2024, 10, e1853.
45. Data-Driven and Intelligent Algorithms for Crack Research in Concrete Structures: A Review. Structures 2025, 75, 108800.