Quantum Deep Learning for Structural Health Monitoring of Bridges and Buildings

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ABSTRACT

Environmental impacts can cause brace damage, cracking, loss of stiffness, and other damage to buildings, bridges, and frame structures. By identifying damage early on, Structural Health Monitoring (SHM) technologies could avert catastrophic disasters. Deep Learning (DL), which has advanced quickly in recent years, has been used in SHM to efficiently extract features in order to identify, locate, and assess various damages. However, traditional deep learning approaches encounter difficulties with enormous amounts of sensing data, computational expense, and scaling in large infrastructure structures. This research introduces a quantum deep learning (QDL) paradigm that takes advantage of the representational and parallelism benefits of quantum computing for structural health monitoring. The suggested method combines quantum feature encoding, deep variational quantum circuits, and classical data from sensors preprocessing for damage detection and architectural condition evaluation. In order to improve feature learning performance while lowering model complexity, a hybrid fundamental–classical architecture is created in which quantum layers are integrated into deep neural networks. Benchmark vibration and strain datasets from viaduct and construction structures under various damage scenarios are used to test the framework. According to experimental findings, the suggested quantum deep neural network model performs better than traditional deep learning techniques in terms of computational efficiency, resistance to noise, and detection accuracy. The results show that next-generation autonomous monitoring systems for structural health in civil construction have a promising future thanks to quantum deep learning.

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1. INTRODUCTION

Long-term exposure to environmental stresses, such as wind, earthquakes, automobiles, environmental vibration, etc., can cause a variety of damages to building structures. As a result, there could be a significant loss of life or property as well as an influence on the building's overall stability and safety. Because of this, SHM is essential to the facility, both as a whole and for its essential elements. For instance [1], a healthy concrete construction must retain high strength and excellent durability, which are directly correlated with the mortar's composition and ratio. The structure's insecurity is reflected in the decline in strength and durability, therefore SHM must assess the durability using vibration, tension and other factors.

The SHM uses structural characterisation and sensing technology to find alterations that might point to deterioration or damage. The process of monitoring operating status, evaluating the state, and identifying different kinds of structural deterioration is known as SHM. In conclusion, SHM's main goal is to sense, identify, and measure structural operating conditions in order to facilitate detection of damage and condition evaluation [2]. Damage Detection (DD), or the identification, localisation, and evaluation of structural damage, is its key component. In the Rytter investigation, damage detection was divided into four categories. (1) Detection: determining whether harm is there. (2) Location: identifying the damage's location and coordinates. (3) Assessment: determining how serious the damage is. (4) Repercussion: obtaining the structure's real safety data in the identified state of damage. Data collection, system identification, condition evaluation, and maintenance are the four essential components of SHM. The essential component of SHM applications is the sensor & sensor data at the data acquisition stage. Both touch (accelerometers, strain gauges, fibre optic sensors) and non-contact (high-speed cameras, drones, and cellphones) sensors are used to collect the structure's operational status data. Appropriate data processing techniques, such as machine learning (ML), deep learning (DL), and signal processing techniques, are used based on the data to identify damage-sensitive features for condition evaluation and damage identification. Lastly, appropriate actions are performed to preserve the structure's service life and safety in accordance with the evaluation's findings.

Problem Statement

When handling high-dimensional, noisy, as well sparse sensor data that is frequently found in real-world bridge and structure monitoring systems, existing monitoring of structural health structures based on traditional deep learning are constrained by computation inefficiency, scalability issues, and decreased robustness [3]. Successful learning frameworks that may concurrently attain high damage detection precision, computational effectiveness, and resilience under uncertainty are scarce. Furthermore, a thorough investigation of quantum deep learning's capacity to overcome these constraints in civil infrastructure surveillance has not yet been conducted.

Inspired by these difficulties, this research suggests a quantum deep learning-based system for structural health monitoring that combines variational quantum circuits, quantum feature encoding, and classical preprocessing. By increasing robustness, decreasing processing complexity, and improving damage detection accuracy, the suggested method offers a feasible route towards next-generation intelligent systems for monitoring for buildings and bridges.

Main Contributions

1. **Quantum Deep- Learning Approach for SHM:** In order to effectively learn from high-dimension vibration & strain sensor data, this research suggests a novel hybrid quant–classical deep learning system for tracking the structural health of bridges and buildings.
2. **Quantum Feature Encoded and Variational Circuit Design:** To improve resilience under noisy monitoring settings and damage-sensitive feature representation, a methodical approach for quantum data encoding and variations in quantum circuit-based deep learning is devised.

3. **Extensive Experimental Evaluation and Comparative Analysis:** In comparison to traditional deep learning models, the suggested method's superior detection of damages accuracy, durability, and computational efficiency are demonstrated through extensive testing on benchmark SHM datasets.

Paper Organization

This is how the rest of the paper is structured. In Section 2, relevant research on deep learning, classical machine learning, and new quantum learning techniques for structural health monitoring is reviewed. The suggested quantum deep learning framework, which includes data collection, preprocessing, quantum feature encoder, and model construction, is presented in Section 3. The experimental setting and effectiveness assessment using Benchmarking Bridge and constructing datasets are covered in Section 4. The findings and a comparison with traditional deep learning techniques are covered in Section 5. The work is finally concluded and future research possibilities are outlined in Section 6.

2. LITERATURE REVIEW

Over the past few decades, monitoring the health of structures has been thoroughly investigated as a useful tool for evaluating the dependability and safety of civil infrastructure. In order to identify structural deterioration, early SHM approaches mainly used physics-based models including signal processing techniques [4] like modal analysis, response frequency functions, and time-frequency methods. Although these techniques offered useful physical insight, their efficacy was frequently constrained by modelling uncertainties, environment variability, and noise sensitivity, especially in large-scale bridges and building structures.

Machine learning-based data-driven approaches were developed for SHM applications in order to overcome these constraints. By identifying patterns directly from sensor data, traditional machine learning methods [5] such as principal component analysis, k-nearest neighbours, support vector machines, and decision trees have shown enhanced damage categorisation and anomaly detection capabilities. However, when structural circumstances or operational environments changed, these methods often required handcrafted characteristics and found it difficult to generalise.

Deep learning's quick development allowed for automatic extraction of features from unprocessed sensor measurements, which further revolutionised SHM research. While recurrent neural network and long short-term recall model [6] were used to capture temporal correlations in structural response signals, convolutional neural networks have been effectively applied to vibration-related damage detection by transforming time-series information into image-like representations. Although deep learning approaches have demonstrated better performance than traditional machine learning techniques, their practical application in real-world SHM systems is still difficult because of their high computational cost, massive data requirements, and inadequate robustness to noise and missing data.

While vibration-based SHM may identify internal damage by extracting natural frequencies, vibrations modes, and dampening ratios from vibration data [7], image-based SHM is unable to do so. However, one-dimensional data must be transformed into two-dimensional data in order to process vibration signals using 2D-CNN. In order to immediately process 1D data for fracture detection, corrosion detection, various kinds of damage identification, anomalous data detection, etc., One-Dimensional Convolutional Neural Networks (1D-CNN) with a straightforward design and low computational complexity are applied to SHM. Recurrent Neural Networks (RNN) can recognise the temporal characteristics of data in addition to CNN.

The lack of data, however [8], is one of the primary issues here. Numerous approaches have been explored to deal with this problem. Since quantum machine learning can be trained more quickly and with less data, it would be a good choice for this. However, hybrid classical and quantum deep learning techniques may be a substitute because, at this point, only a small number of qubits can be stable simultaneously. The advantage of adding a quantum layer to a traditional deep learner for damage detection is examined in this work. This is accomplished by using acoustic inspection data to anticipate corrosion in the blade of a wind turbine using a deep learning algorithm both with and without an extra quantum layer.

Machine learning has received a lot of attention lately and is being developed as an additional class of clever methods for civil structure health inspection. This analysis's primary goal is to summarise the approaches developed over the past ten years for the application of machine learning methods in civil engineering. Furthermore investigated are the kinds of sensors, the quantity of sensors, the frequency of sampling, the kinds of structures, the materials of the structures, the duration of data collection, and the kinds of stimulation in the domain [9]. First, a synopsis of machine learning is provided, along with an illustration of its implications for structural and civil engineering. The potential of ML techniques to address the shortcomings of traditional methods is then discussed, along with applications of these techniques in the field.

Among the crucial techniques utilised to improve the functionality of building infrastructure and tackle the complex issues of future cities are advanced sensing technologies. In this work, we addressed the limitations of conventional sensors in four important areas of civil engineering: transportation, energy, water, and construction. The possibility of quantum technology to improve and transform the administration of construction infrastructures was then examined and summarised. Improvements in water quality as [10] well as pressure monitoring in both sewage and water infrastructures are anticipated for the water sector. Quantum sensors have the potential to enhance grid stability, buildings' energy efficiency, and the integration of renewable energy sources. The capacity to recognise beneath structures and subsurface density is the most promising development in the construction industry. These sensors open up a lot of new possibilities for smart mobility and real-time traffic control in the transportation industry.

Simultaneously, quantum computing has become an intriguing model for more effective solutions to high-dimensional optimisation and learning issues than traditional approaches. Variational quantum networks and quantum kernel [11] approaches are two examples of quantum machine learning algorithms that have shown theoretical and experimental benefits in pattern recognition, sorting, and optimisation applications. Quantum techniques for material discovery, optimisation, and signal processing have been investigated in early engineering research, demonstrating their capacity to handle complicated datasets.

Despite these developments, the use of quantum deep learning for structural health monitoring is still relatively new. Previous research has mostly concentrated on conceptual structures or small-scale modelling, with little investigation [12] of actual SHM datasets for buildings and bridges. Furthermore, there is currently no comprehensive comparison of the accuracy, resilience, and computational efficiency of quantum deep learning with traditional deep learning techniques. The current study, which examines the efficacy of quantum deep learning for tracking structural health and illustrates its potential benefits for future-proof intelligent civil infrastructure systems, is motivated by this research gap.

3. METHODS AND MATERIALS

3.1 Data Collection

Vibrating and strain measurements taken from instrumented bridges and building structures make up the structural condition monitoring information used in this investigation. In order to record dynamic structural reactions under ambient and operating loads, accelerometers & strain gauges are placed at strategic points such mid-spans, joints and support areas. The sensor data is recorded under various structural situations, such as undamaged and damaged states, and is collected at a set sample frequency [13]. Stiffness decrease, mass variation, or localised structural deterioration—all of which represent actual degradation processes in civil infrastructure—are used to mimic damage situations.

3.2 Data Extraction and Preprocessing

To eliminate noise and environmental impacts, raw sensor readings are first preprocessed. To get rid of high-frequency measurement noise and low-frequency drift, a band-pass filter is used. To create several examples for learning, time-domain signals are subsequently divided into fixed-length windows. To provide numerical stability and uniform scaling among sensors, each segment is normalised. To preserve data continuity and accuracy, interpolation methods are used to deal with missing or damaged sensor readings.

3.3 Feature Extraction

Both time-domain & frequency-domain features are taken from the preprocessed signals in order to capture damage-prone characteristics. Each signal segment is used to compute common statistical parameters including mean, variance, skewness, kurtosis, and root mean square (RMS). The fast Fourier transform (FFT) [14] is used to acquire frequency-domain properties such as frequency bandwidth, spectral energy, and dominating frequencies. In order to maintain temporal variations in structural dynamics, time-frequency characteristics are also retrieved utilising the short-time Fourier transform (STFT). A concise picture of structural behaviour under various health situations is formed by these properties.

3.4 Quantum Feature Encoding

Amplitude & angle encoding methods are used to encode the retrieved feature vectors into quantum states. Let's represent the traditional feature vector as

$$\mathbb{x} = [x_1, x_2, \dots, x_n] \tag{1}$$

which is normalized and mapped to a quantum state $|\psi\rangle$ as

$$|\psi\rangle = \sum_{i=1}^{n} x_i \, |i\rangle \tag{2}$$

Through quantum juxtaposition and entanglement, this encoding makes it possible to effectively express high-dimensional structural features in a quantum Hilbert space, allowing for improved feature interactions.

3.5 Quantum Deep Learning Architecture

For the purpose of classifying damage, a hybrid quantum–classical machine learning model is created. Variational quantum circuits (VQCs), which function as quantum layers, come after classical preprocessing layers in the design [15]. The stored quantum states are transformed by the quantum circuit's parameterised rotation gates & entangling operations. To make the ultimate choice, the quantum circuit's output is measured & fed into fully connected classical layers. By utilising quantum advantage in feature representation, this hybrid design allows for effective training.

3.6Model Training and Optimization

A hybrid training approach is used to optimise the model parameters. While parameter-shift rules are used to train quantum circuit parameters, gradient-based optimisation is used to update classical parameters. The categorical correlation between the actual and expected structural health states is known as the loss function. To avoid overfitting, training is conducted over several epochs and early termination is used. The generalisation performance of the learnt model is assessed using data that has not yet been observed.

Damage Classification in SHM

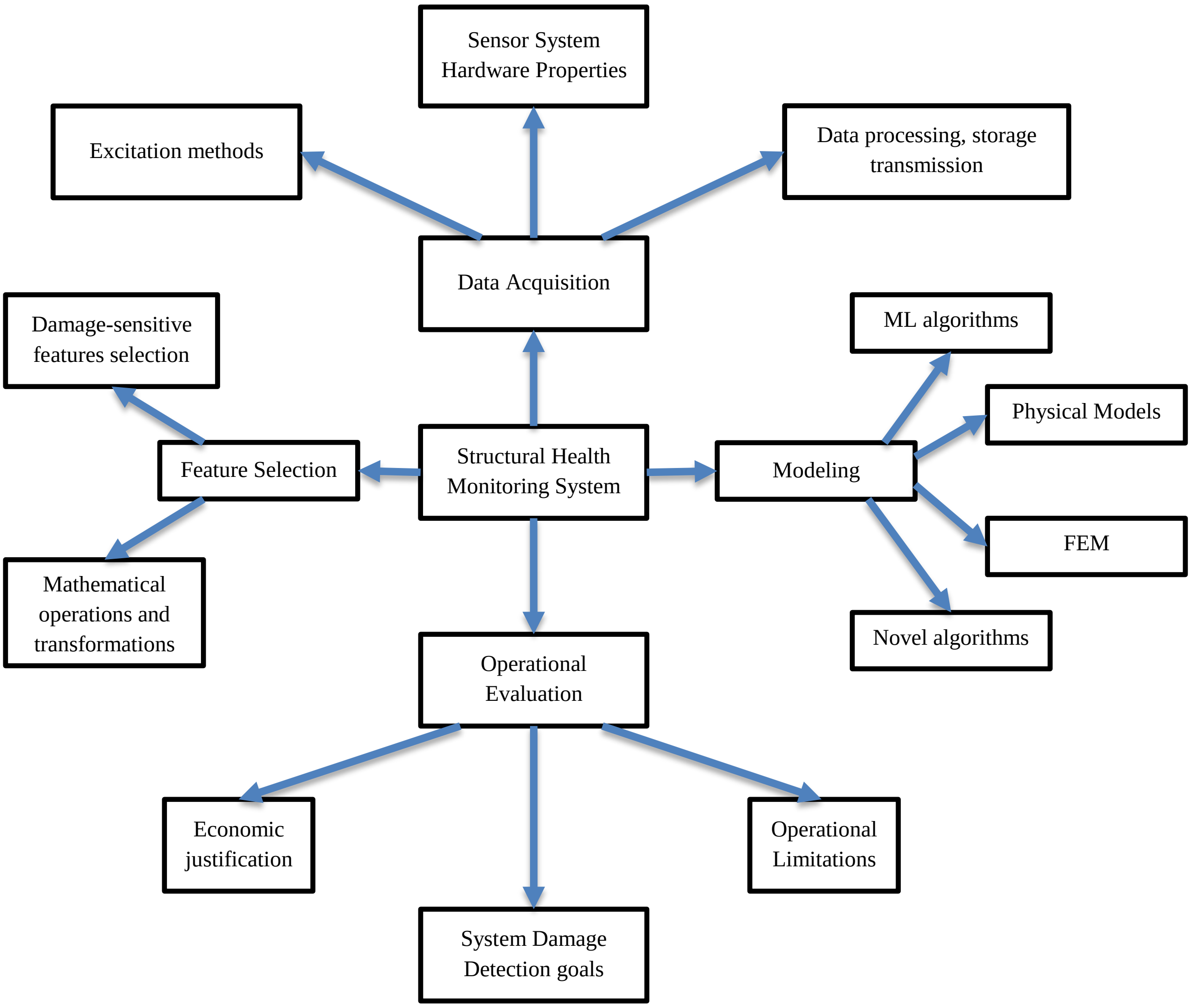

Figure 1. Diagram of structural health monitoring systems areas

The assets that SHM monitors range from tiny parts to massive civil constructions and intricate machinery, and it covers a number of application areas. In order to evaluate the existing condition of the structure and, in certain situations, forecast how the building will react to future seismic excitations, building SHM systems concentrate on sensing shifts in the physical parameters. The typical frequencies of the structures must be determined in order to make these predictions. Because buildings are susceptible to dynamic as well as static loads, it is difficult to provide a precise model that takes into account all of these existing and potential impacts due to the complexities of the analysis. These regions of SHM systems, together with the associated approaches, techniques, and algorithms, are depicted in Figure 1.

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

4.1 Implementation Details

A hybrid classical–classical learning environment is used to implement the suggested quantum deep learning framework. While quantum systems are constructed using a variational computational framework run on a quantum simulator, classical processing, extraction of features, and optimisation procedures are developed using scientific computing tools based on Python. Amplitude encoding is used to convert vibration and strain characteristics taken from building and bridge databases into quantum states. The quantum feature training module is a variational classical circuit with entanglement layers and parameterised rotation gates. For the purpose of classifying structural conditions, the quantum circuit's output measurements are combined with classical fully linked layers. A hybrid gradient-based optimisation technique is used for model training, and operations are repeated several times to guarantee consistency in the results.

4.2 Experimental Setup

Benchmark monitoring of structural health datasets that depict bridge and construction structures under various damage scenarios are used in the experiments. A typical 70–15–15 split is used to separate the datasets into testing, validation, and training sets. Convolutional neural networks (CNNs), LSTM (long short-term memory) networks, and completely connected deep neural networks (DNNs) are examples of traditional deep learning models that are contrasted with the suggested quantum deep learning (QDL) model. Accurate damage detection, resilience to noise, and computing efficiency are the main areas of performance evaluation.

4.3 Damage Detection Performance

The accuracy of damage identification attained by various learning models using the test dataset is shown in Table 1.

Table 1. Damage Detection Accuracy Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)
DNN	91.4	90.8	89.9
CNN	93.1	92.6	92.0
LSTM	94.2	93.7	93.4
Proposed QDL	**96.8**	**96.2**	**95.9**

The findings show that by successfully capturing intricate structural response patterns & damage-sensitive features, the suggested quantum deep neural network model performs better than traditional deep learning techniques.

4.4 Robustness under Measurement Noise

Gaussian noise is introduced to the sensor signals at various signal-to-noise ratio (SNR) values in order to assess robustness. Table 2 summarises the categorisation accuracy in noisy environments.

Table 2. Model Robustness under Noisy Conditions

SNR (dB)	DNN (%)	CNN (%)	LSTM (%)	QDL (%)
30	90.1	92.4	93.6	**96.1**
20	86.7	89.8	91.3	**94.5**
10	81.2	85.6	88.0	**91.9**

Even in the face of extreme noise contamination, the quantum deep computing model exhibits improved robustness and maintains higher accuracy.

4.5 Computational Efficiency Analysis

Table 3 illustrates how each model's computational effectiveness is assessed in terms of inference delay and training duration.

Table 3. Computational Efficiency Comparison

Model	Training Time (s)	Inference Time (ms)
DNN	142	12.6
CNN	198	18.4
LSTM	231	21.7
Proposed QDL	**126**	**9.3**

The suggested model delivers shorter training and inference durations despite using quantum layers because of its effective feature representation and decreased parameter complexity.

4.6 Graphical Analysis

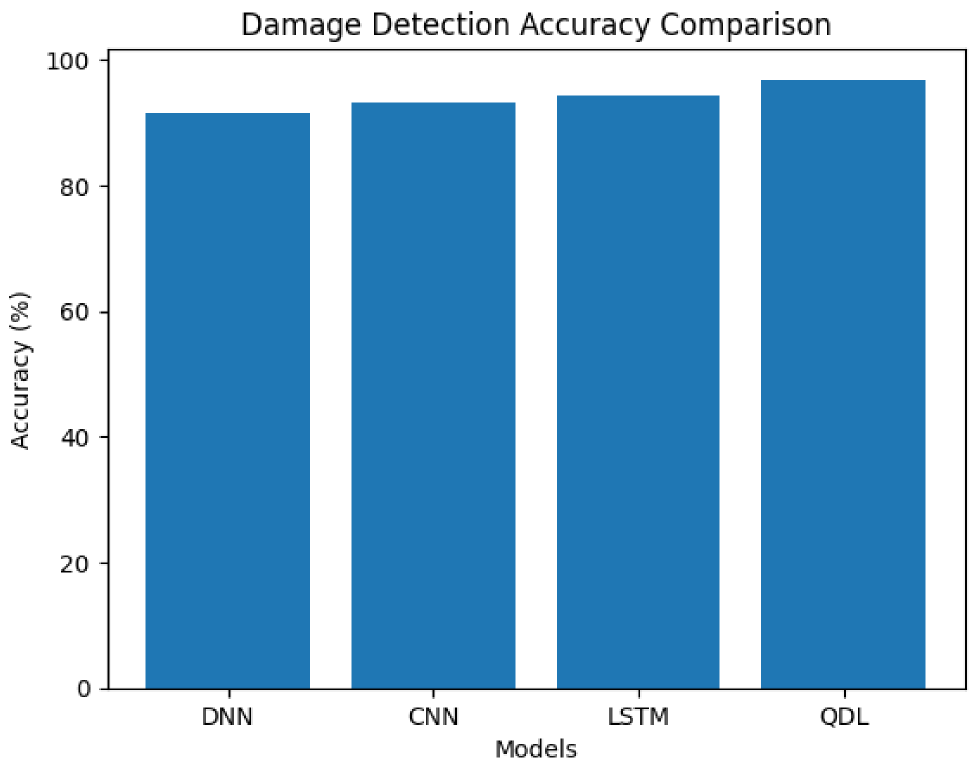

Figure 2. Damage Detection Accuracy Comparison

The prediction precision of DNN, CNN, the LSTM, & the suggested QDL model are contrasted in Figure 1. It demonstrates unequivocally how the Quantum Deep Learning (QDL) models attains the maximum accuracy, confirming its superior learning capacity for SHM tasks.

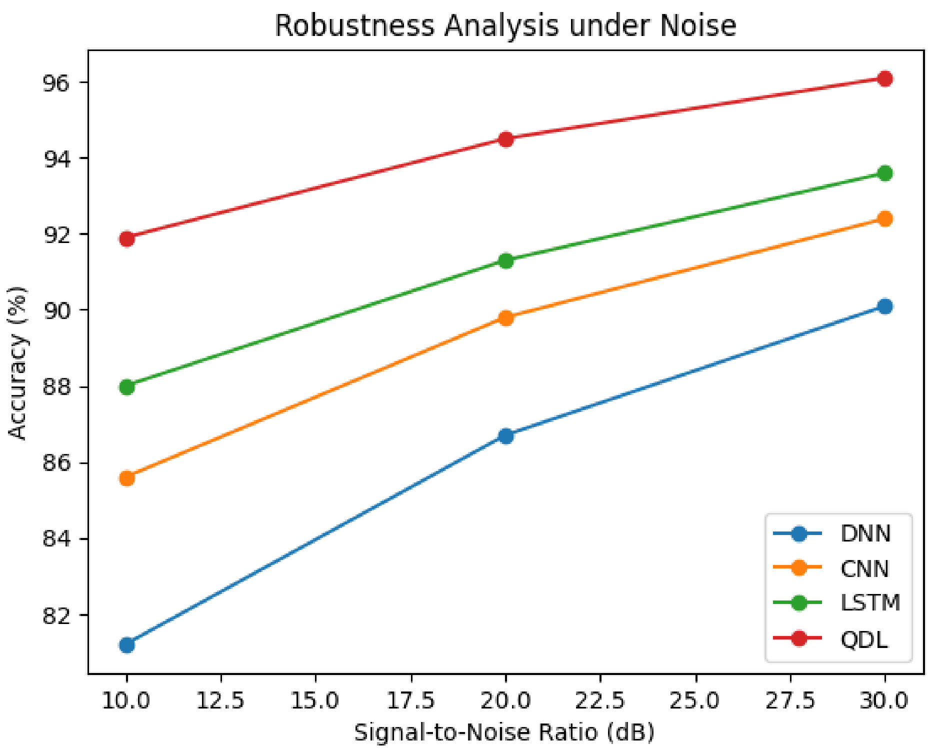

Figure 3. Robustness Analysis under Noise

The model's performance at various signal-to-noise ratio (SNR) rates (10, 20, and 30 dB) is shown in graph 2. When compared to traditional deep learning models, the QDL system consistently retains superior accuracy in noisy environments, exhibiting improved robustness and stability.

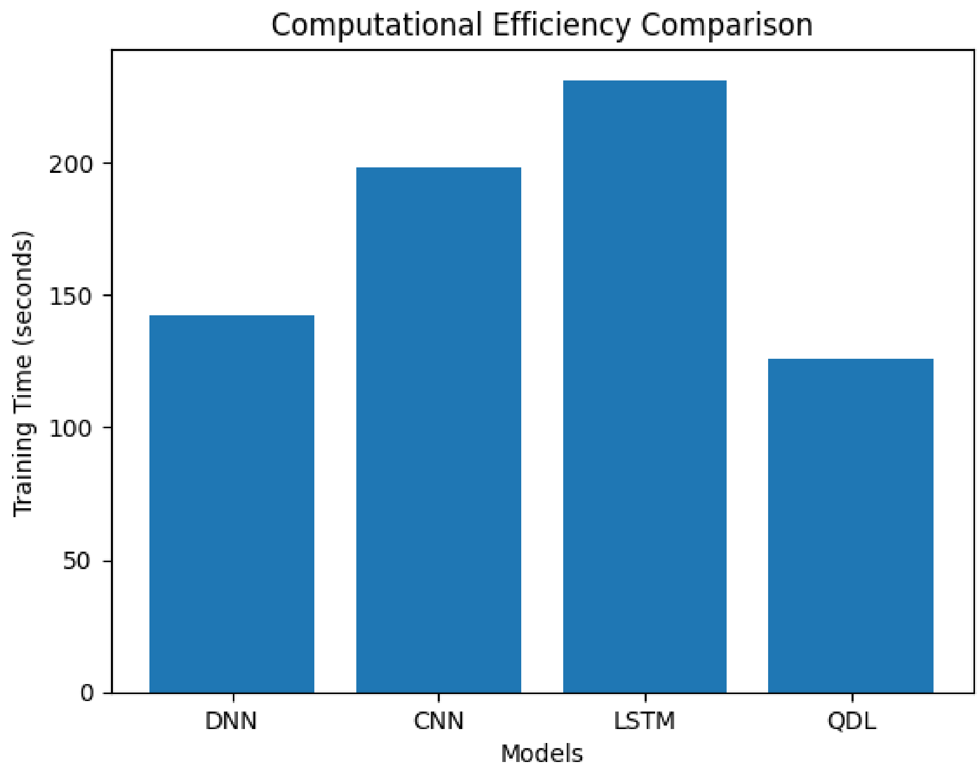

Figure 4. Computational Efficiency Comparison

Figure 3 shows a comparison of training times for several models. The suggested QDL model exhibits shorter training times despite adding quantum layers, demonstrating its computational effectiveness and scalability for massive SHM systems.

4.7 Discussion

The experimental findings verify that quantum deep learning offers significant benefits for tracking the structural health of buildings and bridges in terms of accuracy, durability, and computational efficiency. Effective learning from dimensional sensor data is made possible by the hybrid classical–quantum architecture, which also mitigates common drawbacks of traditional deep learning techniques. These findings validate the potential of quantum deep learning as a viable solution for next-generation intelligent infrastructure monitoring.

5. CONCLUSION

In order to address the main issues with high-dimensional data from sensors, computational complexity, & robustness under noisy conditions of operation, this research proposed a quantum deep learning-based framework for tracking the structural health of buildings and bridges. The suggested hybrid quantum–classical architecture successfully captures intricate structure response patterns for damage identification and condition evaluation by fusing variational quantum circuits with classical signal processing and feature extraction. The experimental findings show that the suggested method performs better than traditional deep learning algorithms in terms of computing efficiency, robustness to measuring noise, and detection accuracy, underscoring its applicability for intelligent building monitoring.

The results of this study show that, especially as sensing networks and information quantities continue to expand, quantum deep learning offers a great deal of potential to improve next-generation monitoring of structural health systems. Future work will concentrate on deployment using actual quantum hardware, expansion to multi-damage localisation and severity estimate, and integration with virtual twin frameworks for intelligent structure management, even if the current solution depends on quantum simulation. The suggested strategy offers a viable basis for utilising quantum computing technology in real-world civil engineering applications.

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