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Quantum Machine Learning for Structural Health Monitoring

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Abstract. Nowadays, employing deep learning for Structural Health Monitoring is a common practice. However, one of the main challenges here is the lack of data. Several methods have been developed to address this issue. Quantum machine learning is known to be trained faster and with less data, therefore, it could be a suitable option to be used for this purpose. However, since at the current stage limited numbers of qubits can remain stable at the same time, hybrid quantum-classical deep learning approaches can be a replacement. In this study, the benefit of incorporating a quantum layer into a classical deep learner for detecting damage is investigated. For this purpose, a deep learning model with and without a quantum layer is used to predict damage in a wind turbine blade by using ultrasonic inspection data. The results indicate the benefit of employing hybrid quantum-classical ML in detecting damage.

1. Introduction

Nowadays, machine learning is being used extensively for monitoring the quality of a component throughout its life cycle. This includes Non-Destructive Testing (NDT) [1] and Structural Health Monitoring (SHM)[2]. However, there are several challenges in this effort among which two cases are particularly crucial: data shortage and long training time. Researchers address the former by different approaches such as fusion at the data [3] or decision level [4], and by incorporating the physics of the problem through a hybrid cost function or by generating synthetic data from a finite element model [5]. These approaches may increase the overall training time.

With the advancement of quantum computers and the associated algorithms, different fields have started to exploit inherent quantum mechanical features such as superposition and entanglement and investigate if these effects can be leveraged in their field. Among various quantum-related research areas, quantum machine learning (QML) is one of the promising domains because of its ability to achieve faster convergence with smaller datasets than classic ML [6]. This is one of the main reasons for its recent widespread applications [7, 8, 9]. Despite this progress, implementing QMLs in real applications is very challenging due to the limited number of qubits that can remain stable at the same time.

To overcome this limitation, researchers developed hybrid quantum-classic machine learning approaches that combine the strength of both classical and quantum algorithms. For instance, classical machine learning algorithms can be used for data preprocessing and reducing the complexity of problems, while quantum computing can be used to speed up computations and optimizations that could be intractable to classical computers. These approaches thus, have the potential to enable more efficient and accurate analysis of complex data sets, as is in SHM, leading to better and faster decision-making.

In this study, a preliminary investigation have been conducted on the application of Hybrid Quantum-Classical ML to structural health monitoring. It should be emphasized that the primary focus is on developing an ML model that could perform better than a classical ML model on a set of SHM data, rather than on the generalization capability and interpretability of the model obtained. In this regard, in Section 2, a short background on pertinent topics in quantum machine learning is provided. In Section 3 hybrid quantum-classic model will be introduced and in Section 4, it will be applied to ultrasonic inspection and the relevant results will be shown. Section 5 will conclude the paper.

2. Background on quantum computing

In this section, some pertinent information about quantum computing will be presented. Quntumbit, or qubit, is the smallest piece of quantum information which is a complex vector pointing to a unit sphere, i.e. Bloch sphere. Mathematically, its state is shown by Bra-Ket notation and can be in state 0 as $|0\rangle = \begin{bmatrix}1 & 0\end{bmatrix}$, 1 as $|1\rangle = \begin{bmatrix}0 & 1\end{bmatrix}$, or in a superposition state as $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$ where $\alpha, \beta \in \mathbb{C}$ and $|\alpha^2| + |\beta^2| = 1$

To change the state of a quantum state, unitary transformation U is needed to map the state ψ to ϕ as,

$$|\phi\rangle = U|\psi\rangle \tag{1}$$

The transformation U is unitary if $UU^\dagger = U^\dagger U = I$ with I as an identity operator. The unitary transformations can make quantum gates that can act on 1 or more qubits. The list of common gates is shown in Table 1. In this table, besides their name and their representation, their matrix form, number of inputs, and a short description of each gate are presented. For instance, Pauli gates rotate their input for 90 degrees about their corresponding axes. The Hadamard gate transforms a qubit from the computational basis ($|0\rangle$ and $|1\rangle$ like classical information) to the superposition state. This means when it is applied to a qubit in the $|0\rangle$ (resp. $|1\rangle$) state, the qubit transforms to $|+\rangle = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$ (resp. $|-\rangle = \frac{1}{\sqrt{2}}(|0\rangle - |1\rangle)$).

The quantum gates can be parameterized and then connected to each other to make a quantum machine learning model [10]. For instance, the Pauli gates can be parameterized by their rotation angles. These parameterized gates together with their matrix representations are shown in Table 2.

After making a parameterized quantum model, measurement is required to extract classical information from a quantum state. One technique is based on the σ_z expectation. σ_z is the matrix shown in Table 1 as Pauli-Z that acts on a single qubit.

The expectation value of the σ_z operator for a qubit in state $|\psi\rangle$ is given by:

$$\langle\sigma_z\rangle = \langle\psi|\sigma_z|\psi\rangle \tag{2}$$

This expression calculates the average result we would obtain if we were to perform many measurements of the qubit in the σ_z basis. For example, if we have a qubit in the state $|\psi\rangle = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$, then the expected value of the σ_z operator is:

$$\langle\sigma_z\rangle = \langle\psi|\sigma_z|\psi\rangle = \frac{1}{\sqrt{2}}\begin{pmatrix}1 & 1\end{pmatrix}\begin{pmatrix}1 & 0\\ 0 & -1\end{pmatrix}\frac{1}{\sqrt{2}}\begin{pmatrix}1\\ 1\end{pmatrix} = 0$$

3. Hybrid Quantum-Classical ML

As mentioned, hybrid quantum-classical ML is being developed as a response to leverage the quantum properties in classical methods. Depending on where, how and to what extent the

Table 1: Important quantum gates and their representations

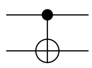
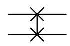
Quantum gates	**Matrix**	**Representation**	**Input**	**Description**
Identity	$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$	$-\boxed{I}-$	1 qubit	Does nothing
Pauli-X (σ_x)	$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$	$-\boxed{X}-$	1 qubit	Rotation around X-axis
Pauli-Y (σ_y)	$\begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix}$	$-\boxed{Y}-$	1 qubit	Rotation around Y-axis
Pauli-Z (σ_z)	$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$	$-\boxed{Z}-$	1 qubit	Rotation around Z-axis
Hadamard	$\frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$	$-\boxed{H}-$	1 qubit	Superposition
CNOT	$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$		2 qubits	Entanglement
SWAP	$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$		2 qubits	Swap two qubits

Table 2: Parameterized Quantum Gates

Quantum gates	**Matrix**	**Parameters**	**Applications**
R_x	$\begin{bmatrix} \cos\frac{\theta}{2} & -i\sin\frac{\theta}{2} \\ -i\sin\frac{\theta}{2} & \cos\frac{\theta}{2} \end{bmatrix}$	θ	Rotation around X-axis
R_y	$\begin{bmatrix} \cos\frac{\theta}{2} & -\sin\frac{\theta}{2} \\ \sin\frac{\theta}{2} & \cos\frac{\theta}{2} \end{bmatrix}$	θ	Rotation around Y-axis
R_z	$\begin{bmatrix} e^{-i\frac{\theta}{2}} & 0 \\ 0 & e^{i\frac{\theta}{2}} \end{bmatrix}$	θ	Rotation around Z-axis
U3	$\begin{bmatrix} \cos\frac{\theta}{2} & -e^{i\phi}\sin\frac{\theta}{2} \\ e^{i\lambda}\sin\frac{\theta}{2} & e^{i(\lambda+\phi)}\cos\frac{\theta}{2} \end{bmatrix}$	θ, ϕ, λ	Universal gate

quantum algorithms and/or layers are employed to enhance classical methods, different hybrid approaches have been developed as discussed in [11].

In this work, a hybrid model is made by adding a quantum layer to a classical deep learning model. The classical part of the model consists of two Convolution layers, two ReLU activation layers, two Maxpool layers, and one Dropout as shown in Fig.1. The outcome of the Dropout layer will be fed to two fully connected (FC) layers. The configuration of this part of the model is presented in Table 3. The second FC layer has one output that will be sent to the quantum layer shown in Fig. 2 as q.

The chosen quantum layer shown in Fig. 2 is a simple quantum circuit consisting of two gates: Hadamard gate H and the rotation gate R_y. The Hadamard gate was chosen to impose the superposition to the input data q and then R_y gate that has one parameter, i.e. the rotation angle θ as shown in Table 2, to be able to make some adjustment for fitting to the data. In the end, a measurement was performed based on σ_z expectation as shown in Eq. (2). This is a standard measurement approach in most of quantum algorithm.

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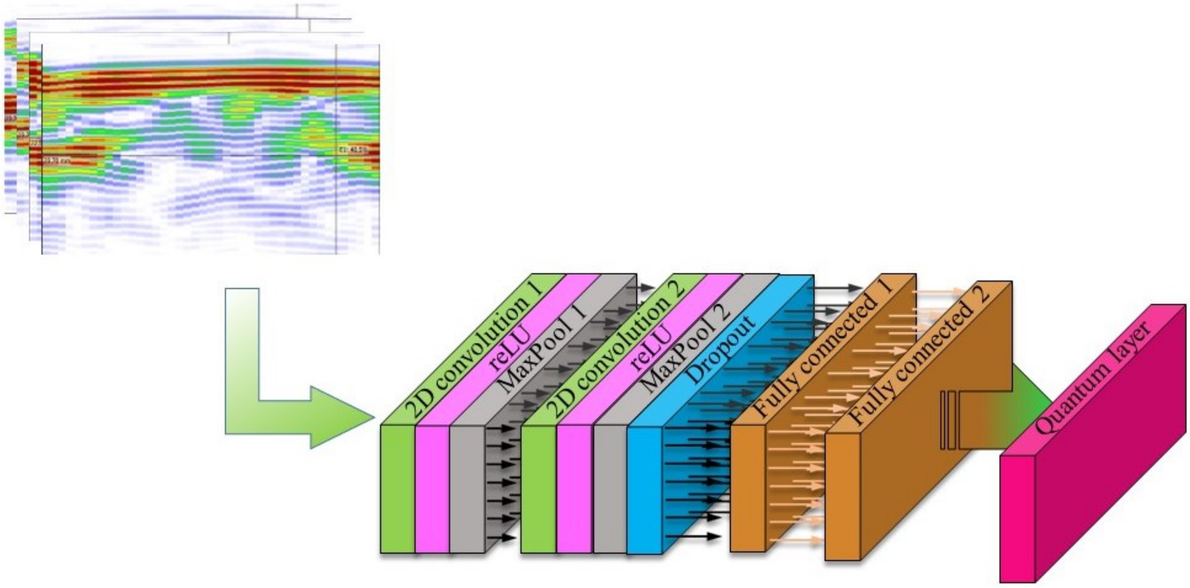


Figure 1: The CNN model used in this study. The parameters of the classic part of the model is presented in Table 3 and the quantum layer is shown in Fig 2

Table 3: Configuration of the classical part of the hybrid model shown in Fig. 1

Layer	**Properties**
Convolution 1	10 filters, kernel size 11x11, activation function ReLU
Max Pool 1	Pool size 2x2
Convolution 2	16 filters, kernel size 6x6, activation function ReLU
Max Pool 2	Pool size 2x2
Dropout	Dropout rate of 0.20
Fully Connected 1	784 neurons, activation function ReLU
Fully Connected 2	64 neurons, activation function ReLU, 1 output: q in Fig. 2,

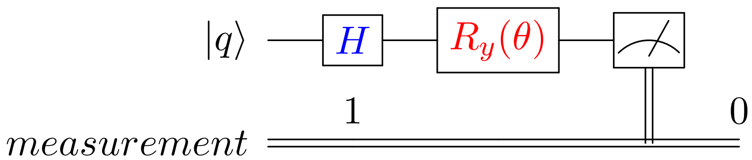


Figure 2: The employed quantum layer consisting of a Hadamard gate H and R_y gate. The measurement will then be done by the σ_z expectation

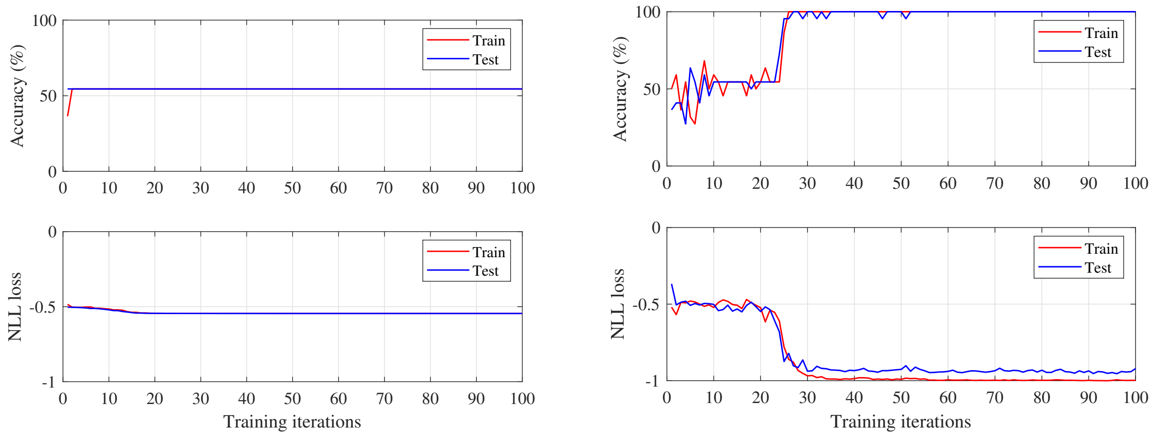
After making the model, the Adam optimization algorithm will be employed to estimate the unknown parameters.

4. Application to the ultrasonic inspection

Ultrasonic inspection is one of the common techniques for SHM to detect damage. This technique has been used for damage detection in a wind turbine blade made of glass fiber-reinforced polymer (GFRP). In this analysis, the ultrasonic signals were captured through the pulse-echo method using a phased array probe composed of 50 transducer elements sending the pulse at a 0.5 MHz frequency.

To generate a dataset for training the model shown in Fig. 1, a portion of these images collected at the location of the bonding area between skin and spar caps have been used. From all the collected images, 44 images have been chosen: 20 healthy and 24 damaged. The dataset has been divided into 50% training and 50% test. It should be emphasized here that the number of healthy/damaged images and the train/test portions have been selected to simulate complex situations for learning models.

To illustrate the importance of the quantum layer in the hybrid model, the performance of the same model without the quantum layer has also been analyzed. In this model, the second fully connected layer (FC2) gives two outputs that will be fed to the Softmax layer for making decisions. This model will be referred to as the classical model. Both classical and hybrid models have been trained by the Adam optimizer together with the negative log-likelihood loss function [12].



(a) Classic network (b) Hybrid network

Figure 3: Convergence analysis of the networks

Fig.3 illustrates the convergence of the hybrid model and the classic model on the train (red line) and test (blue line) datasets. As can be seen in Fig. 3a, the classical model got stuck in a local minimum of "*all damaged*" with the accuracy of 54.5% on the train and test datasets whereas, the hybrid model was converged to 100% accuracy on the train and test datasets after about 25 iterations, as shown in Fig. 3b.

Statistical analysis

In order to provide a thorough comparison between the performance of the hybrid model and its classical counterpart, a statistical analysis has been devised. For this purpose, the whole procedure of generating random training datasets and training the models have been repeated 100 times. The performance of the models are shown in Fig. 4. In these figures, the training procedure of all the 100 models is shown individually in the background while the mean (solid lines) and median (dashed lines) of the accuracies are shown in the foreground.

As can be observed, in most cases, the classic model with the softmax couldn't move and got stuck in the local minimum of "*all damaged*". But the hybrid model, in most cases, jumps out of the local minimum and converge to close to 100% accuracy in the test datasets. Therefore, the mean of the accuracy is about 80% for both training and test datasets and the median of the accuracies converges to 100% for training datasets and above 90% for test datasets.

This statistical analysis clearly shows the importance of the quantum layer for making non-complex models, especially with small training datasets.

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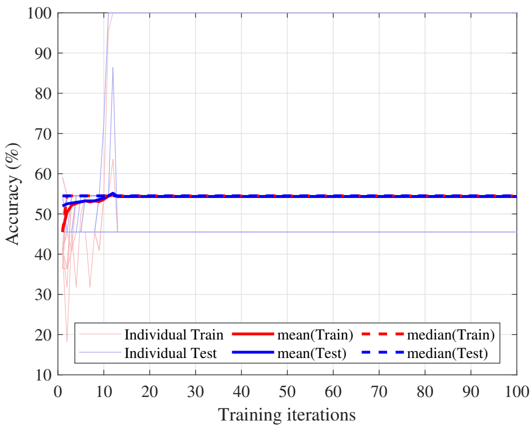
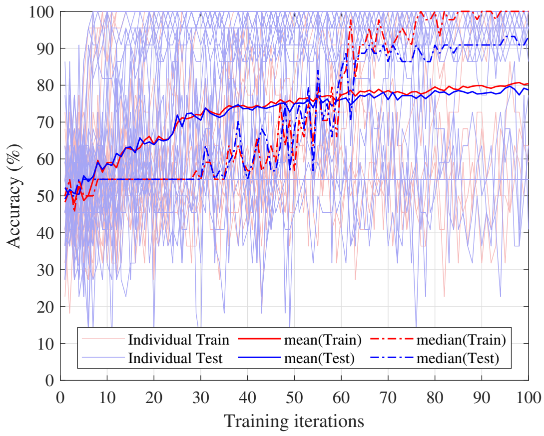


(a) Classical network



(b) Hybrid network

Figure 4: Statistical analysis of the models' performance

5. Conclusion

In this study, the benefit of hybrid quantum-classical machine learning to the filed of structural health monitoring has been demonstrated. In this regard, the performance of two models have been compared in detecting damages: i) a classical deep learner and ii) a hybrid model with the same classic learning part together with a simple quantum layer. Both models have been trained on an experimental dataset obtained by performing ultrasonic inspection of a wind turbine blade.

The results indicate that the dataset is too complex for the classic model and got stuck in a local minimum. But, the hybrid quantum-classic model could jump over the local minimum and converges to the median accuracy of above 90% on the test dataset. It should be emphasized that, the generalization capability and interpretability of the model were not the focus of this work.

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References

[1] Yaghoubi, V., Cheng, L., Van Paepegem, W., Kersemans, M.: An ensemble classifier for vibration-based quality monitoring. Mechanical Systems and Signal Processing 165, 108341 (2022)

[2] Nokhbatolfoghahai, A., Navazi, H.M. and Groves, R.M., 2022. Use of dictionary learning for damage localization in complex structures. Mechanical Systems and Signal Processing, 180, 109394, (2022)

[3] Eleftheroglou, N., Zarouchas, D., Loutas, T., Alderliesten, R., Benedictus, R.: Structural health monitoring data fusion for in-situ life prognosis of composite structures. Reliability Engineering & System Safety 178, 40–54 (2018)

[4] Yaghoubi, V., Cheng, L., Van Paepegem, W., Kersemans, M.: A novel multi-classifier information fusion based on dempster–shafer theory: application to vibration-based fault detection. Structural Health Monitoring 21(2), 596–612 (2022)

[5] Cross, E.J., Gibson, S., Jones, M., Pitchforth, D., Zhang, S., Rogers, T.: Physicsinformed machine learning for structural health monitoring. In: Structural Health Monitoring Based on Data Science Techniques, pp. 347–367. Springer (2022)

[6] Huang, H.Y., Broughton, M., Cotler, J., Chen, S., Li, J., Mohseni, M., Neven, H., Babbush, R., Kueng, R., Preskill, J., McClean, J.R.: Quantum advantage in learning from experiments. Science 376(6598), 1182–1186 (dec 2021)

[7] Eskandarpour, R., Bahadur Ghosh, K.J., Khodaei, A., Paaso, A., Zhang, L.: Quantum-enhanced grid of the future: A primer. IEEE Access 8, 188993–189002 (2020)
[8] Cao, Y., Romero, J., Olson, J.P., Degroote, M., Johnson, P.D., Kieferová, M., Kivlichan, I.D., Menke, T., Peropadre, B., Sawaya, N.P., Sim, S., Veis, L., Aspuru- Guzik, A.: Quantum Chemistry in the Age of Quantum Computing. Chem. Rev. 119(19), 10856–10915 (oct 2019)
[9] Jia, B., Pham, K., Chen, G., Shen, D., Wang, Z., Wang, G., Blasch, E.: Quantum technology for aerospace applications. In: Sensors and systems for space applications VII. vol. 9085, pp. 194–199. SPIE (2014)
[10] Benedetti M, Lloyd E, Sack S, Fiorentini M.: Parameterized quantum circuits as machine learning models. Quantum Science and Technology 4(4), 043001, (2019).
[11] Metawei, M.A., Said, H., Taher, M., Eldeib, H. and Nassar, S.M., 2020, November. Survey on hybrid classical-quantum machine learning models. In 2020 International Conference on Communications, Computing, Cybersecurity, and Informatics (CCCI), pp. 1-6, IEEE (Nov. 2020).
[12] https://qiskit.org/textbook/ch-machine-learning/machine-learning-qiskitpytorch. html