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Rotating machinery health state diagnosis through Quantum Machine Learning

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Academia and enterprises have explored Prognostic and Health Management (PHM) to perform the diagnosis of failure modes via several traditional Machine and Deep Learning methods. However, the computation scenario is heading toward new advances, which include Quantum Processing Units. Due to its promising results in terms of speed and scalability, research centers worldwide began experimenting with models that lay at the intersection of machine learning and quantum computing. In this sense, a new technique that has already been applied in different scenarios is Quantum Machine Learning (QML), which aims to improve conventional methods in terms of performance and results. This work aims to apply QML models for the fault diagnosis of bearings, an important rotating machinery component, by vibration signals. We apply hybrid models involving the encoding and construction of parameterized quantum circuits connected to a classical neural network. The study uses rotation gates and different entanglement gates (CNOT, CZ and *i*SWAP), and explores the impact of varying the number of the quantum circuits layers. We perform a classical Multilayer Perceptron model for comparisons purposes. We use the database Case Western Reserve University with 10 failure modes. The obtained results suggest that, despite the current limitations of quantum environments, QML models are promising tools to be further investigated in PHM activities.

Keywords: Quantum Machine Learning. Rotating Machinery. Health State Diagnosis. Variational Quantum Algorithm.

1. Introduction

Rotating machinery is a critical industry equipment that operates in complex environments subject to high temperatures, fatigue, and large loads (Song et al., 2018). Vibration analysis has become the industry standard for evaluating the condition of this type of equipment. Traditional methods for diagnosing failure modes, in the context of Prognostic and Health Management (PHM), include feature extraction using signal processing methods and defect classification adopting Machine Learning (ML) and Deep Learning (DL) approaches.

A field that has been gaining space in the literature is Quantum Computing, as well as the algorithms developed within this framework with the aim of promoting improvements in problem solving, such as PHM (Maior et al., 2023). The so-called Quantum Machine Learning (QML) combines quantum computing techniques to the classical ML models. Among these, the concept of qubits, or quantum bits, which are the smallest quantum units, is highlighted. The qubits can admit the states "0", "1", or a linear combination of both, called superposition (Correa-jullian et al., 2022). Furthermore, entanglement operations allow strong correlations to be established between qubits regardless of the distance between them (Correa-jullian et al., 2022). Therefore, the objective of this work is to investigate and adapt QML models to perform PHM, through the diagnosis of failure modes, of bearings as the rotating equipment components.

2. Methodology overview

Our QML models were constructed via TensorFlow Quantum library and runed in the Cirq quantum simulator without consider noise. The framework to develop the QML models is divided in four main steps, as follows:

(1) Prepare Quantum Dataset: we preprocess the classical data by normalizing and extracting features – in this case, mean, variance, root mean square (RMS), peak to peak, kurtosis, maximum amplitude, skewness, and crest factor. Then, the data is encoded into qubits via angle encoding method where N qubits defined in a $|0\rangle$ state.

(2) Evaluate quantum model: after encoding the data, PQC is created with different architectures. The first one consists only of rotation gates over y, x, and z, for each qubit with parameterized angles. In addition, we considered a circuit configuration with a Euler (composed by R_y, R_z, R_y) followed by a nearest-neighbor qubit coupling using the different entanglement gates (CNOT, CZ, and *i*SWAP). PQCs were built with different numbers of layers (1, 5, and 10). The maximum number of layers was 10 due to computational limitations.

(3) Sample: measurements are performed, returning the processed quantum data to classical data. For this work, a measurement operation was defined through the Pauli Z-gate $\left(Z = \begin{bmatrix}1 & 0\\0 & -1\end{bmatrix}\right)$ in each of the qubits.

(4) Evaluate classical model: it collects the built features that are fed to the neural network. Error backpropagation and diagnosis are performed.

4. Results

In Table 1, we can observe the results for the thirteen models performed in this study. The metric analyzed is the Recall. The classic MLP has the worst recall (91.95%). The best result consists of the configuration of PQC with CZ and five layers (98.47%), which is approximately six percentage points greater than MLP. The CNOT configurations, among all the QML structures applied in this research, have the lowers results.

Table 1. Recall results.

Category	Quantum gates	# of circuit layers	Recall
Classic MLP	-	-	91.95
QML	Ry, Rx, Rz	1	97.32
		5	95.02
		10	96.93
	Ry, Rz, Ry + CNOT	1	94.25
		5	95.02
		10	95.79
	Ry, Rz, Ry + CZ	1	96.93
		5	98.47
		10	96.55
	Ry, Rz, Ry + iSWAP	1	96.93
		5	95.79
		10	96.93

We performed the Kruskall-Wallis statistical test to evaluate the null hypothesis that “the medians of the balanced accuracies of the models are equal”. In other words, we want to assess whether the balanced accuracy scores vary based on the "model" factor. As shown in Table 2, the null hypotheses were rejected since the statistics exceed the critical value (21.0261). Thus, we can infer that, statistically, at least two medians among the models differ and the balanced accuracy scores vary based on the model factor. Certain models consistently demonstrate suboptimal performance, particularly those utilizing CNOT. On the other hand, some models, such as the architecture with CZ, exhibit superior results.

Table 2. CWRU: Kruskal-Wallis test results.

Metrics	CWRU
	8 features
H_{obs}	47.9495
pvalue	3.19e-06

5. Conclusion

There are now a lot of restrictions on how much computing power quantum programs have. Nonetheless, this is a potential route that frequently gains ground in businesses and academia. For example: another metrics can be compared, such as precision and accuracy; different PQC and Neural Networks structures; other backpropagation and encoding methods; and, run the models in a real quantum hardware.

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References

Correa-Jullian, C., S. Cofre-martel, G. S. Martin, E. L. Droguett, G. de N. P. Leite, and A. Costa (2022). “Exploring Quantum Machine Learning and Feature Reduction Techniques for Wind Turbine Pitch Fault Detection”, Energies, vol. 15, no. 8.

Maior, C. B. S., L. M. M. Araujo, I. D. Lins, Moura, M. J. C. and E. L. Droguett (2023). “Prognostics and Health Management of Rotating Machinery via Quantum Machine Learning”, IEEE Access.

Song, L., H. Wang and P. Chen (2018). “Vibration-Based Intelligent Fault Diagnosis for Roller Bearings in Low-Speed Rotating Machinery”, IEEE Transactions on Instrumentation and Measurement, vol. 67, no. 8, pp. 1887–99.