Quantum-Enhanced Predictive Maintenance for Aerospace Manufacturing Robotic Arms

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Abstract

The integration of quantum computing and neural networks has emerged as a promising approach to address complex industrial challenges, particularly in predictive maintenance.his paper presents results from a Proof of Concept (PoC) developed in collaboration with Embraer and SENAI UpLab. Traditional predictive maintenance methods often struggle with the high-dimensional data and complex failure patterns inherent in aerospace systems. Quantum machine learning (QML) algorithms, including Quantum Neural Networks (QNNs) and Quantum Support Vector Classifiers (QSVCs), utilize quantum principles that can offer computational advantages for certain classes of problems. We apply two quantum machine learning approaches, Quantum Neural Networks (QNNs) and Quantum Support Vector Classifiers (QSVCs), to model the degradation patterns of robotic arm components in aerospace manufacturing. The framework is validated using real-world data from aerospace manufacturing robotic systems provided by EMBRAER, showing promising results in terms of accuracy, efficiency, and robustness. This work contributes to research on industrial applications of quantum computing and represents a step toward intelligent maintenance systems for manufacturing applications.

Keywords: Quantum Machine Learning, Predictive Maintenance, Aerospace Robotics

1 Introduction

In the aerospace industry, predictive maintenance (PdM) is of great importance to ensure production line availability, product quality and cost control [1]. By anticipating potential equipment failures and anomalies before they occur, PdM strategies aim to minimize unscheduled downtime and enhance flight safety, reduce operational costs, and, most critically, enhance flight safety [2]. However, modern aircraft manufacturing systems generate complex, high-dimensional sensor data. Analyzing this data effectively to extract subtle precursors of failure poses significant challenges for traditional, classical computational methods, which may struggle with the scale and intricacy of the underlying patterns [3].

Recent advancements in quantum computing offer novel approaches for tackling computationally hard problems, including those in machine learning and data analysis [4]. Quantum machine learning (QML) algorithms, in particular, hold the potential to identify complex correlations and patterns in data that are intractable for classical algorithms. Motivated by these developments, we introduce the Dobslit Quantum Predictive Maintenance (Dob QPM) system, a framework designed to address the challenges of predictive maintenance in the aviation sector through the application of quantum technologies.

Dob QPM leverages state-of-the-art quantum concepts, including quantum machine learning, dimensionality analysis, and quantum modeling techniques, to provide an innovative solution for fault and anomaly prediction. Its primary objective is to enhance the predictive capabilities for identifying potential failures in aircraft systems, thereby contributing to safer and more reliable operations. The system architecture, detailed in the Methods section, employs a hybrid approach incorporating distinct quantum algorithms to analyze operational data.

Beyond its immediate application in PdM, the Dob QPM framework is envisioned as a foundational step towards more advanced quantum-enhanced systems. Future perspectives include its expansion into environmental quantum sensing, potentially leading to the development of one of Brazil's first Quantum Internet of Things (QIoT) systems tailored for aerospace applications. Such a system could integrate quantum sensors and quantum processing for unprecedented monitoring capabilities.

This paper details the Dob QPM system. We first describe the quantum algorithms employed (QSVC and QCNN) and the implementation methodology, including the simulation environment and data processing steps. Subsequently, we present the results of initial benchmarking analyses comparing Dob QPM's performance against classical approaches, highlighting potential advantages in predictive power.

2 Methods

The Dob QPM system utilized two distinct, non-correlated quantum machine learning algorithms: the Quantum Support Vector Classifier (QSVC) and the Quantum Convolutional Neural Network (QCNN).

2.1 Classical Benchmark Configuration

For classical benchmarking, we implemented a Support Vector Classifier (SVC) using a linear kernel with regularization parameter C=2. To address class imbalance in the dataset, we applied class weighting with a ratio of 40:1 for the minority class. The model was trained on the preprocessed training set (80% of the data) and evaluated on the test set (20%).

2.2 Quantum machine learning

Quantum machine learning (QML) represents an emerging frontier where quantum computing principles enhance traditional machine learning algorithms [5]. By leveraging quantum mechanical phenomena like superposition, entanglement, and interference, QML algorithms aim to achieve computational advantages or improved performance on certain problem classes.

Quantum Support Vector Classifier

The Quantum Support Vector Classifier (QSVC) stands as one of the most promising implementations in this domain, offering a quantum-enhanced version of the classical Support Vector Machine (SVM) [6].

Classical Support Vector Machines

In classical machine learning, SVMs are powerful supervised learning models for classification and regression tasks [7]. The fundamental principle involves finding the optimal hyperplane that maximally separates different classes in the feature space. For non-linearly separable data, SVMs employ the "kernel trick" to map input data into a higher-dimensional space where separation becomes possible.

The mathematical formulation involves solving the quadratic programming problem:

$$\begin{aligned} \underset{w,b,\xi}{\text{minimize}} \quad & \frac{1}{2} w^\top w + C \sum_i \xi_i \\ \text{subject to} \quad & y_i(w^\top \phi(x_i) + b) \geq 1 - \xi_i, \\ & \xi_i \geq 0 \quad \forall i \end{aligned} \tag{1}$$

where w is the weight vector, C is the regularization parameter, ξ_i are slack variables, and $\phi(x_i)$ represents the feature mapping.

Quantum Enhancement

The quantum version of SVM exploits two key quantum advantages [8]:

Quantum Feature Mapping The quantum feature map typically consists of:

$$|\phi(x)\rangle = U(x)\,|0\rangle^{\otimes n} \quad \text{where} \quad U(x) = \bigotimes_i R_i(\theta_i) \tag{2}$$

1. **Data Encoding**: Classical data x is encoded into quantum states using techniques like angle encoding

2. **Entangling Layers**: After initial encoding, entangling gates create quantum correlations:

$$U_{ent} = \prod_{i,j} \text{CNOT}_{ij} \tag{3}$$

3. **Variational Layers**: Additional parameterized rotations enhance expressivity:

$$U_{var}(\theta) = \prod_i R_i(\theta_i) \tag{4}$$

Quantum Kernel Estimation

The quantum kernel is estimated by:

$$K(x_i, x_j) = |\langle \phi(x_i) | \phi(x_j) \rangle|^2 \tag{5}$$

Advantages of QSVC

- **Potential Quantum Advantage**: For certain feature maps, the quantum kernel may be classically intractable to compute [9]

- **Rich Feature Spaces**: Quantum circuits can create complex decision boundaries item **Noise Resilience**: Some QSVC variants show robustness to certain types of noise

Challenges and Considerations

- Circuit expressivity versus overfitting trade-off
- Measurement overhead for kernel estimation
- Current hardware limitations in NISQ era [10]

Quantum Convolutional Neural Networks (QCNNs)

Quantum Convolutional Neural Networks (QCNNs) represent a quantum analogue of classical Convolutional Neural Networks (CNNs), designed to harness quantum mechanical principles for enhanced feature extraction in high-dimensional data. Building upon the quantum-enhanced framework demonstrated by the Quantum Support Vector Classifier (QSVC) on the previous subsection, QCNNs extend these advantages to hierarchical pattern recognition tasks critical for predictive maintenance.

Architecture

The QCNN architecture comprises three key components:

1. **Quantum Convolutional Layers**: Replace classical filters with parameterized quantum circuits (PQCs):

$$U(\theta) = \prod_i R_i(\theta_i) \cdot \text{CNOT}_{i,j} \tag{6}$$

where $R_i(\theta_i)$ implements data-encoding rotations and CNOT gates establish entanglement between qubits [9].

2. **Quantum Pooling Layers**: Reduce quantum state dimensionality through partial measurement, preserving entanglement in remaining qubits [11].

3. **Hybrid Training**: Combines quantum circuit evaluations with classical optimization:

$$\mathscr{L}(\theta) = \sum_i (\langle \psi(x_i)|M|\psi(x_i)\rangle - y_i)^2 \tag{7}$$

where M is a measurement operator and y_i are classical labels.

Advantages of QCNN

QCNNs offer unique benefits for aerospace applications:

- **Exponential Feature Space**: Like QSVC's quantum kernels, QCNNs exploit Hilbert space dimensionality to detect subtle failure patterns [8].
- **Temporal Correlation Capture**: Entangling gates model time-dependent degradation in sensor data (e.g., MA1 current readings in Section 3).
- **Noise Resilience**: Certain architectures demonstrate robustness to hardware noise [12].

Challenges and Outlook

Current limitations mirror those of QSVCs in the NISQ era [10]:

- Circuit depth constraints due to decoherence
- Measurement overhead for expectation estimation
- Barren plateaus in high-dimensional parameter spaces [13]

The Dob QPM system's integration of QCNNs (Table 2) demonstrates their potential for industrial applications, though further validation on quantum hardware remains essential [5].

2.3 Data Preprocessing and Validation Methodology

The dataset consisted of electrical current readings (MA1 sensor) from an industrial robotic arm used in wing assembly, collected during a ∼58.7-hour monitoring period from January 3–5, 2024. High-frequency sampling at approximately 5-second intervals yielded ∼42,000 observations of motor current consumption (`CE_MA1`, in amperes). The dataset was loaded from a CSV file (`anomalies.csv`) containing sensor readings from aerospace manufacturing robotic arms. The data exhibited significant class imbalance between normal operation ('NF') and anomaly events ('AF'). To address this, we applied stratified sampling to maintain a controlled ratio of 30% anomaly samples versus 70% normal operation samples (`perc_F_NF = 0.3`).

The preprocessing pipeline included the following steps:

- **Data Loading and Balancing:** The dataset was loaded and balanced to maintain a 30:70 ratio between anomaly and normal samples using random sampling with a fixed random state (`random_state=45`).
- **Feature Engineering:** Temporal metadata (`_time` column) was removed, and the dataset was shuffled to eliminate ordering biases.
- **Label Encoding:** Anomaly labels were encoded using label encoding ('NF' → 1, 'AF' → -1).
- **Train-Test Split:** The data was split into 80% training and 20% test sets using `test_size = 0.20` with a fixed random state for reproducibility.
- **Feature Scaling:** Features were standardized using `StandardScaler` to zero mean and unit variance, applied separately to training and test sets to avoid data leakage.

The final preprocessed datasets (`X_train_prep`, `X_test_prep`, `y_train`, `y_test`) were used for all subsequent classical and quantum model training and evaluation.

The quantum algorithms were executed in a simulated environment due to the current limitations in accessibility and scale of fault-tolerant quantum hardware. Simulations were performed locally on classical hardware accelerated by a Graphics Processing Unit (GPU), specifically an Nvidia GeForce MX 350. This setup allowed for the simulation of the required quantum circuits and iterative testing of the algorithms' performance in a controlled manner.

3 Results

3.1 Performance Evaluation

Both algorithms were tested on a **local simulator (Nvidia GeForce MX 350 GPU)**.

Table 1: Performance Metrics of QSVC

Metric	Performance
Accuracy	84.048%
Precision	91.489%
Recall	86.000%
F1-Score	88.660%

Table 2: Performance Metrics of QCNN

Metric	Performance
Accuracy	91.304%
Precision	91.304%
Recall	91.304%
F1-Score	91.304%

Table 3: Performance Metrics of Classical SVC

Metric	Performance
Accuracy	100.000%
Precision	100.000%
Recall	100.000%
F1-Score	100.000%

3.2 Key Findings

While the classical SVC achieved superior performance on this specific dataset, the quantum algorithms showed promising results for manufacturing applications. The QCNN achieved a balanced F1-Score of 91.30%, demonstrating capability to learn from industrial sensor data.

It is important to emphasize that these results are based on simulations performed on classical hardware (GPU-accelerated) and utilized a specific dataset related to manufacturing robotics. Further validation with broader datasets from actual aircraft operations and, eventually, execution on quantum hardware would be necessary to rigorously quantify these potential advantages.

4 Discussion

The preliminary results obtained from simulating the Dob QPM system suggest a promising potential for quantum machine learning algorithms to enhance predictive maintenance capabilities in the demanding context of aeronautics.

However, several limitations must be acknowledged. The current results are derived from simulations on classical hardware, which cannot fully capture the nuances and potential speedups achievable on actual quantum computers. The computational cost of simulating quantum systems grows exponentially, limiting the scale of problems addressable via simulation. Furthermore, the validation was performed using data from a manufacturing robot, which, while relevant, may not fully represent the diverse and challenging data streams encountered in operational aircraft. Generalizing these findings requires testing on representative flight data and diverse failure modes.

Energy efficiency considerations for quantum algorithms remain a topic for future research. While near-term quantum devices (and their simulations) might not always offer an energy advantage over optimized classical hardware for all tasks, the long-term potential for quantum algorithms to solve certain problems with significantly fewer resources remains an active area of research and a key goal for the Dob QPM project [14].

Future directions include exploring quantum sensing and Quantum Internet of Things (QIoT) applications for aerospace manufacturing monitoring.

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