Hybrid Quantum Convolutional Neural Network for CNC Machine Bearing Fault Detection Using Vibration and Acoustic Signals

[1]Nallabariki Praveen Kumar, [2]Swetha G, [3]Lakshmanarao A, [4]Gururaj L Kulkarni, [5]Sreenivasulu Gogula and [6]Koti Reddy M

[1]Department of Computer Science and Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana, India.
[2]Computer Science and Engineering, R R Institute of Technology, Chikbanavara, Bangalore, Karnataka, India.
[3]Department of Information Technology, Aditya University, Surampalem, Andhra Pradesh, India.
[4]Department of Artificial Intelligence and Machine Learning, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India.
[5]Department of Information Technology, Vardhaman College of Engineering, Hyderabad, Telangana, India.
[6]Department of Electronics and Communication Engineering, Universal College of Engineering and Technology, Guntur, Andhra Pradesh, India.
[1]praveenkumar_n@vnrvjiet.in , [2]Swetha.ganganala@gmail.com, [3]laxman1216@gmail.com
[4]gururajlkulkarni@gmail.com, [5]gsrinivasulu1678@vardhaman.org, [6]kotiucet@gmail.com

Correspondence should be addressed to Nallabariki Praveen Kumar: praveenkumar_n@vnrvjiet.in

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Abstract – Flexible manufacturing systems (FMS) rely heavily on CNC machine tools, and the machines' failure can be attributed to bearing failure. Bearing fault detection is critical in avoiding machine downtime and expediting expensive repair work. To enhance the precision of CNC machine bearing failure detection via vibration and sound signals, the present research suggests a Hybrid Quantum Convolutional Neural Network with Skill Optimization Algorithm (QCNN-SOA). For enhanced defect classification, the method integrates a skill optimization technique with quantum convolutional networks. Preprocessing of signals is performed using the SWVO-RKF to eliminate noise and outliers without distorting fault-related patterns. The Inception Convolutional Vision Transformer (ICVT) model is used for feature extraction to capture local and temporal dependencies. Hybrid QCNN is employed to classify features that are extracted. A classical fully connected layer is employed for classification after employing quantum gates for convolution and encoding of the signal. With an error rate of 0.8%, the proposed method achieves 99.2% accuracy, 99.6% recall, 98.7% precision, and 99.1% F1-score.

Keywords – Bearing Fault Detection, Inception Convolutional Vision Transformer, Robust Kalman Filter, Skill Optimization Algorithm, Quantum Convolutional Neural Network.

I. INTRODUCTION

Machine tools with computer numerical control (CNC) are essential to contemporary manufacturing systems, especially Flexible Manufacturing Systems (FMS), where extremely high precision and adaptability are essential. Many different parts must cooperate for these CNC machine tools to execute intricate tasks. Bearing is one among them that are critical to the operation of a machine [1]. The bearings in a CNC machine enable the various moving components to rotate and, if it fails, then the production can be severely compromised. Bearing failure is one of the primary causes of downtime and maintenance costs in CNC machines; hence early diagnosis is critical in maintaining operational integrity and ensuring longevity of the machine [2]. In order to reduce unexpected failures and maintain high production standards, bearing defects must be detected early. Vibrations and sound signals produced during operation offer invaluable information for this purpose. In spite of the minimal size, bearings operate in challenging conditions and are often exposed to intense loads, wear, and friction during the operation of machines. They are more susceptible to degradation due to long working hours and fluctuating environmental conditions [3]. If detected in an early stage, the harm may prevent further dangerous defects from emerging by triggering strange vibrations and sound emissions. However, the early-stage symptoms of bearing faults are subtle and often buried in noise, making detection a difficult task. The signals generated by defective bearings are typically weak and easily masked by background noise from other machine components, complicating traditional fault diagnosis approaches. Moreover, the unpredictable operational conditions in CNC machines, including varying load conditions, speed fluctuations, and external disturbances, further increase the difficulty of accurately identifying faults.

Nonetheless, diagnosing such a fault is not an easy procedure. The noises caused by other mechanisms within the equipment often swamp the signals given out by defective bearings. In addition, bearing failures can occur in non-linear, time-varying, and non-stationary forms as a result of the complexity of modern CNC machine tools, which operate under different load conditions and speeds [4].

The ability to distinguish between these weak fault signals and noise is the key challenge in detecting bearing failure, especially under fluctuating operating conditions. Initial bearing degradation typically takes the form of slight, mostly imperceptible vibration and acoustic signal changes [5]. Frequency domain-based faults have been identified through traditional methods like Fast Fourier Transform (FFT)and Time-Synchronous Average (TSA). Yet, due to the fact that they may not be able to sufficiently represent the transient, non-stationary nature of initial bearing degradation, these methods often fail to detect incipient failures. Newer methods like Empirical Mode Decomposition (EMD), Short-Time Fourier Transform (STFT) and Wavelet Transform (WT), have been employed in a bid to get over this limitation [6-8]. These techniques have the ability to examine the time-frequency properties of the signal with improved resolution for fault detection at different levels of degradation**.** Despite these advancements, traditional approaches still face challenges related to computational efficiency, model complexity, and the need for manual feature extraction, which can limit their scalability in real-time industrial applications [9]. CNNs are now effective tools in fault diagnosis, processing intricate data from vibration and acoustic signals. They are capable of learning hierarchical features from raw sensor data, differentiating between normal and faulty states [10-14]. This has resulted in smart fault detection systems, giving early warnings, reducing downtime, and enhancing CNC machine health monitoring. Early detection prolongs machine operational life and saves on maintenance costs, allowing predictive maintenance schedules [15-17]. However, CNNs have limitations in handling complex signal variations, and their reliance on extensive labelled datasets increases computational burdens [18]. Additionally, CNN struggle with extracting fine-grained local and temporal features from vibration signals, reducing their overall effectiveness in noisy environments. Existing models encounter challenges in effectively learning local and temporal features from signals, leading to limitations in fault detection and classification accuracy for CNC machines. Additionally, they struggle with noise robustness and computational efficiency, affecting overall model performance. In order to address the issue of fault detection in flexible manufacturing systems this study suggests a hybrid quantum CNN model for bearing failure diagnostics. The model is dynamic in nature, detecting faults at the earliest possible stage. Quantum computing offers significant advantages by leveraging quantum parallelism, which allows for efficient processing of high-dimensional data and improved pattern recognition. Integrating quantum principles into CNN architectures enhances their ability to capture intricate variations in fault signals, leading to superior detection accuracy.

Novelty and Contribution,

- For detecting bearing issues in CNC machines through vibration and acoustic inputs, a hybrid quantum convolutional neural network with skill optimization algorithm (QCNN-SOA) is proposed.
- The SWVO-RKF is applied to remove noise and outliers for more effective fault identification.
- The Inception Convolutional Vision Transformer (ICVT) is utilized to learn local and temporal features from signals using convolutional layers and multi-head attention mechanisms.
- Quantum gates are used for encoding, convolution, and pooling, and a classical fully connected layer for fault classification to enhance detection accuracy.
- SOA is used to optimize QCNN hyperparameters to increase overall model performance and fault classification accuracy.
- The new method dramatically enhances fault detection accuracy, noise robustness, and computational efficiency compared to the conventional deep learning models.

This organizational structure is employed in the study: A summary of the literature on this topic is provided in Section 2. Section 3 offers a clear explanation of the methods employed. The results of employing these strategies are illustrated in Section 4. The findings of the research are corroborated by the explanations analyzed in Section 5.

II. LITERATURE SURVEY

Convolutional Neural Network based fault diagnosis technique which detects CNC machine problems during their early stages was described in 2022 by Iqbal and Madan [19]. Acoustic and vibration signals undergo STFT-based conversion to generate their time-frequency representations before processing. The proposed system achieved superior results compared to traditional diagnostic methods when assessing bearing faults in CNC machines according to extensive testing results. The CNN-based method far outperformed the performance of Artificial Neural Networks (ANN) and other traditional machine learning techniques. The results confirm the efficacy of the CNN-based fault detection approach, rendering it a potential candidate for early fault diagnosis in CNC machine bearings Iqbal et al. [20] in 2024 introduced a new framework for the identification of bearing faults in CNC machines to tackle previous challenges. The technique consists of an experimental setup to obtain raw vibration and acoustic signals, which are converted into time-frequency maps via the STFT. The CNN extracts advanced features from maps that get used to train an MSVM based fault classifier. Research results demonstrated that the method achieved peak classification precision through the combination of vibration and acoustic signals. The approach delivered superior results compared to existing cutting-edge methods by enhancing classification precision and processing efficiency for CNC machine-bearing fault diagnosis.

Iqbal and Madan [21] introduced a vibration-based smart condition and fault diagnosis method to determine bearing faults of CNC machines. The procedure incorporates experimental vibration analysis to obtain the structure of defect monitoring and defect classification for the bearing defects. By applying Hybrid Signal Decomposition, the vibration signal undergoes decomposition before unnecessary characteristics are eliminated through the use of Principal Component Analysis (PCA). The selected attributes proceed for classification through Gentle AdaBoost and Discrete AdaBoost. The experimental results reveal Discrete AdaBoost to deliver superior performance than Gentle AdaBoost as well as other machine learning techniques. The method demonstrates strong potential to stop unexpected CNC machine breakdowns which result from bearing failure. Xue et al. [22] presented a digital twin-based approach for diagnosing CNC machine tool faults. Making and confirming the CNC machine tool's digital twin model is the first step in the procedure. A collection of twin models is created, which includes many models in various defective states. A model selector learns from model data fusion that uses the CART decision tree method for training. Model selection from the library for defect diagnostic purposes is accomplished by using real sensor data through the picker. The approach is used to diagnose spindle stiffness degradation in CNC machine tools and proves its effectiveness and practicability in fault detection and operation monitoring.

Kumar, P. et al. [23] developed a fault identification model for Direct-Shift Gearboxes to detect and diagnose CNC machine tool faults. This model uses a Convolutional Neural Network (CNN) with Variational Mode Decomposition (VMD) techniques. The kurtosis values for each VMD mode were 2.95, 3.02, 11.99, 3.04, 2.92, and 3.02. A drawback of VMD is that it requires careful tuning of parameters, such as the number of decomposition modes and penalty factors. Kale, A. P., et al. [24] developed a Deep Belief Network for tool fault recognition to identify variations in the milling operation that lead to tool faults. The network learns from the STFT spectrogram of tool conditions and classifies the recognized pattern into one of six classes. The classification accuracy is 90.83% in cross-validation mode. Limited generalization is a drawback of this system. He, J. et al. introduced a novel AI approach utilizing a deep belief network (DBN) for unsupervised fault diagnosis in gear transmission chains. To enhance the network’s structural optimization, a genetic algorithm was employed. The proposed method achieved fault classification accuracies of 99.26% for rolling bearings and 100% for gearboxes. However, its generalization capability may be compromised if the dataset is limited, biased, or does not adequately represent real-world fault scenarios.

Problem Statement

The main CNC machine maintenance challenge lies in early detection and fault diagnosis of the bearings, one of the prevalent machine failure causes. If these faults go undetected, they may result in unplanned stops, and therefore, efficiency and reliability during production are impaired. Conventional methods of detecting faults tend to be inaccurate and do not translate to real-time implementation, a scenario that discourages bearing-type failure prevention within CNC machines. This problem calls for the establishment of a sophisticated diagnostic method capable of accurately detecting and diagnosing bearing faults in real time from vibration and acoustic signals to allow CNC machine tools to keep operating smoothly.

III. PROPOSED METHODOLOGY

The detection method of CNC machine bearing faults through Hybrid Quantum Convolutional Neural Network with Skill Optimization Algorithm (QCNN-SOA) requires the acquisition of vibration and sound signals using two accelerometers. The first is installed radially on the outer race, while the second is axially fixed and rotates along with the planet carrier. These signals are pre-processed using the Sliding Window Variational Outlier-Robust Kalman Filter (SWVO-RKF), which effectively removes noise and outliers and enhances fault detection through the use of a sliding window and variational Bayesian methods. The ICVT model performs feature extraction after preprocessing by employing convolutional layers together with multi-head attention processes to identify temporal along with local patterns in the signals. Lastly, the features extracted are fed into a Hybrid Quantum CNN for classification, where quantum gates are employed for signal encoding, convolution, and pooling, and then a classical fully connected layer for fault categorization, yielding enhanced fault detection accuracy. To optimize the Hybrid QCNN hyperparameters, Skill Optimization Algorithm (SOA) is employed. The proposed architecture is described in **Fig 1**.

Data Collection

Initially, two accelerometers were used to gather the vibration and sound signals from the CNC machining center. The external accelerometer mounted radially on the outside race of the bearing received placement while the internal accelerometer attached axially to the planet carrier. Data was acquired during the CNC process with variable torque loading of 30, 50, and 70 Nm while maintaining a constant shaft speed of 14 Hz. To diagnose faults, these gathered signals were sent to preprocessing, where they were filtered and processed.

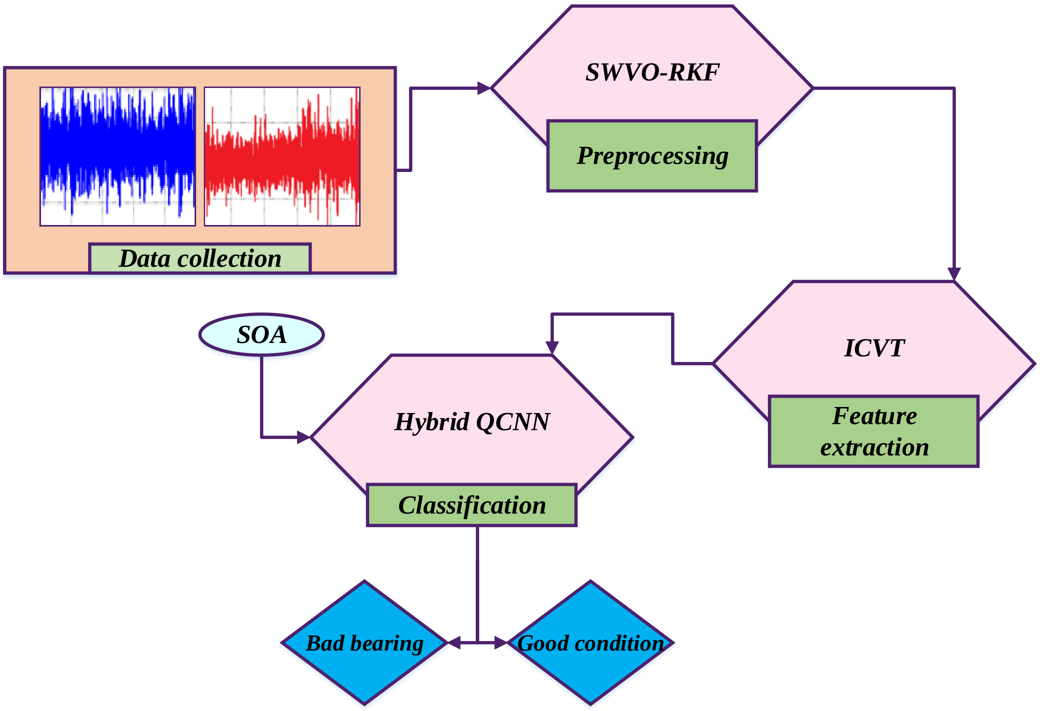


Fig 1. Proposed Hybrid QCNN For CNC Machine Bearing Fault Detection.

Preprocessing Using Sliding Window Variational Outlier-Robust Kalman Filter

The Sliding Window Variational Outlier-Robust Kalman Filter (SWVO-RKF) [13] can be quite helpful in this application since it can eliminate outliers and noise from the signals while still generating precise state predictions. This method is designed to address the complex, noisy, and outlier-prone vibration and acoustic data derived from CNC machine bearings. The SWVO-RKF method increases the sensitivity of fault identification by employing a variational Bayesian technique that iteratively refines the state estimates using a sliding window of data and models noise as heavy-tailed distributions. The Student's t-distribution serves as the noise generation model to replicate field signals with outliers and ensure the accuracy of the monitoring system as shown in equation (1).

$$\begin{cases} r\left(z_l \middle| z_{l-1}, S_m\right) = \delta u\left(z_l; H_l z_{l-1}, S_m, \omega\right) \\ \qquad = \int O\left(z_l; H_l z_{l-1}, S_m / \xi_l\right) I\left(\xi; \omega/2, \omega/2\right) f\xi_l \\ r\left(b_l \middle| z_{l-1}, W_m\right) = \delta u\left(b_l; E_l z_l, W_m, \vartheta\right) \\ \qquad = \int O\left(b_l; E_l z_l, W_m / \lambda_l\right) I\left(\lambda_l; \vartheta/2, \vartheta/2\right) f\lambda_l \end{cases} \tag{1}$$

The system state at time m, represented by hidden states and noisy vibration measurements, is modeled by the transition matrix H_l and the measurement matrix I. The noise covariance matrices S_m and E_l are updated adaptively using Inverse Wishart distributions for dynamic noise estimation during detection, as described in equation (2).

$$\begin{cases} s\left(T_n \middle| b_{1:m-N}\right) = J\omega\left(T_m; \hat{a}_{m|m-N}, \hat{A}_{m|m-N}\right) \\ s\left(W_m \middle| b_{1:m-N}\right) = J\omega\left(W_m; \hat{q}_{m|m-N}, \hat{Q}_{m|m-N}\right) \end{cases} \tag{2}$$

Iteratively adapting to changing noise conditions in CNC machines, the Inverse Wishart ($J\omega$) distribution is utilized to update previous noise covariance beliefs for vibration and auditory inputs. This adaptive estimator takes operating state changes into account to enhance fault identification. The system states and bearing problems get assessment with variational inference through an approximate distribution of system states and noise parameters. This method facilitates efficient computing by using a factorized approximation of the joint posterior, as described in equation (3).

$$r\left(\Theta_m \middle| a_{1:m}\right) \approx s\left(z_{m-M:m}\right)s\left(S_m\right)s\left(T_l\right)s\left(\xi_{m-N+1:m}\right)s\left(\lambda_{m-M+1:m}\right) \tag{3}$$

Where, Θ_m represents the set of all variables, which includes the auxiliary noise variables ξ and λ, the noise parameters $\left(S_m\right)$, $\left(T_l\right)$, and the system states $\left(z_{m-M:m}\right)$. These components' factorized distributions are represented by the variational approximation s . The SWVO-RKF effectively uses variational inference to estimate the posterior distribution of the states and noise parameters.

Feature extraction using Inception Convolutional Vision Transformer (ICVT)

The Inception Convolutional Vision Transformer (ICVT) model [14] initiates exploration of features in vibration and acoustic inputs through soft split token embedding (SSTE). To extract local spatial information, an input y_{j-1} of size $I_{j-1} \times X_{j-1} \times D_{j-1}$ is processed through a convolutional layer. The feature map's output size is calculated using equation (4).

$$I_j = \left\lfloor \frac{I_{j-1} - T + 2q}{t} \right\rfloor + 1, X_j = \left\lfloor \frac{X_{j-1} - T + 2Q}{t} \right\rfloor + 1 \tag{4}$$

Following the convolution, the new spatial dimensions I_j and X_j are computed using this equation. Training is then stabilized by using layer normalization once the feature map has been flattened to a 1D vector. By doing this, the feature dimension is increased and the sequence length is decreased, creating a bigger receptive field for complicated signal patterns. The depth-wise convolutional transformer block is then used. A depth-wise convolution applies to the 2D map using kernel size $t \times t$ after input tokens achieve this transformation. The flattened tokens proceed to the multi-head attention module before they are converted back to 1D form. The expression is described in equation (5).

$$y_j^{r/l/w} = flatten\left(conv2D\left(reshape2D\left(y_j\right), t\right)\right) \tag{5}$$

In this case, $y_j^{r/l/w}$ stands for the token inputs for the multi-head attention mechanism's query, key, and value matrices. Compared to linear projections, the depth-wise convolution (Conv2D) model is more efficient since it reduces the number of parameters while capturing local context. By capturing both local features and intricate temporal patterns, the ICVT model is able to handle vibration and acoustic signal data efficiently before applying it to classification.

Classification Using Hybrid Quantum CNN

The extracted dimensional time-series signal, represented as $t_1, t_2, ..t_n$ over time, is the input to the Hybrid QCNN [15] for signal categorization. Usually, a small window is created from the signal, and each window is analyzed separately. For a quantum gate, each signal value t_j acts as a parameter. Qubits are initialized by applying the signal values as rotation angles, which encodes the signal. The encoding procedure for a signal is represented by equation (6).

$$\left|\psi\right\rangle = \alpha\left|00\right\rangle + \beta\left|01\right\rangle + \gamma\left|10\right\rangle + \delta\left|11\right\rangle \tag{6}$$

These complex numbers, which stand for the probability amplitudes of various basis states, are $\alpha, \beta, \gamma\ and \delta$. The quantum state is altered by unitary operations performed on the quantum system after the signal data has been encoded. Together with their transformation capabilities the alterations function within random as well as variational quantum circuits. After the system is subjected to a unitary gate V , the quantum state can be represented using equation (7).

$$V\left|\psi\right\rangle = V\left(\alpha\left|00\right\rangle + \beta\left|01\right\rangle\right) \tag{7}$$

Where, a parameterized quantum circuit could define the unitary transformation, denoted by V . The quantum system functions on tiny portions of the signal data at the quantum convolution layer. Apply the quantum convolution on a 2×2 quantum window for a signal. Applying quantum gates to the qubits performs the quantum convolution operation. The computation of each convolution operation is done using equation (8).

$$|\psi\rangle = \alpha|00\rangle + \beta|01\rangle \tag{8}$$

A new quantum state is subsequently created by mapping the convolution result to the learned properties of the signal. The application of the quantum convolution process is followed by a quantum pooling operation, which is analogous to max-pooling in CNNs. The quantum state is lowered in this method by measuring certain qubits and extracting expectation values. Assume that the output of the quantum convolution is $|r_{out}\rangle$. Apply a measurement A on the quantum state to pool the data, as indicated in equation (9).

$$F = \langle\psi_{out}|A|\psi_{out}\rangle \tag{9}$$

Where, A is operator. The expectation value F represents the result of the pooling procedure, which captures the most important characteristics of the signal. Measurement introduces nonlinearity into quantum systems. Once the quantum state has evolved, it is broken into one of its foundation states via a measurement. The measurement result yields classical results. Additional classification through analysis takes place after data processing by the quantum convolutional and pooling layers by sending the expectation values to a classical fully connected layer. The output from the quantum layers is described by equation (10), which is a vector of expectation values.

$$F = \langle\psi_{signal}|V^{+}(A_1,..A_O)WV(\theta)|\psi_{out}\rangle \tag{10}$$

A classical fully connected layer receives the expectation values F from the quantum convolutional and pooling layers. Unitary operations $V(\theta)$ and W, as well as measurement operators $A_1,..A_O$, are used to compute these expectation values. These features are subsequently mapped to certain fault categories by the traditional fully connected layer, which categorize the fault.

Hyperparameter Optimizing Using Skill Optimization

Hyperparameter tuning is an important process of optimizing Hybrid Quantum CNN models for better performance. The Skill Optimization Algorithm (SOA) [16] can be used to optimize hyperparameters efficiently by considering them as decision variables in the search space. A candidate solution is a potential set of hyperparameters, and the objective function measures their efficacy in terms of model accuracy or loss. SOA seeks the search space in two phases: Exploration and Exploitation. The exploration phase, where every candidate solution learns from an expert (a higher performing member), leads towards promising areas. The exploitation phase optimizes the solution via local searches and hyperparameter adjustment to further enhance performance. Through this iterative cycle, a trade-off between global exploration and fine-tuning within the local regions is maintained. The algorithm chooses the optimal performing hyperparameter setting after a specified number of iterations. Leveraging SOA, optimization of hyperparameters becomes more effective, avoiding exhaustive grid or random search. The adaptive learning strategy improves the convergence rate without causing premature stagnation. Below is the algorithm 1 for hyperparameter optimization using SOA.

Algorithm 1. Hyperparameter Optimization Using SOA

Initialize population Y randomly within given hyperparameter search space

for each candidate solution Y_j:

for each hyperparameter dimension e:

$y_{j,e} \rightarrow randomvaluewithinitsbounds$

Evaluate the objective function G for each candidate solution Y_j

 # Phase 1: Skill Acquisition from Experts (Exploration)

for each candidate solution Y_j do:

Identify the set of better solutions (experts set)

Randomly select an expert F_j from this set (not necessarily the best)

Update position:

$YQ1_{j,e} = y_{j,e} + s \times (F_{j,e} - J \times y_{j,e})$

If new position improves objective function:

$Y_j \rightarrow YQ1_j$

#Phase 2: Skill Improvement through Practice (Exploitation)

for each candidate solution Y_j do:

Update position based on local search:

if $s < 0.5$:

$YQ2_{j,e} = y_{j,e} + ((1-2s)/u) \times y_{j,e}$

else:

$YQ2_{j,e} = y_{j,e} + ((mc_k - 2s)/u) \times y_{j,e}$

If new position improves objective function:

$Y_j = YQ2_j$

Update the best and worst candidate solutions

Increment iteration counter u

Return the best candidate solution as the optimal hyperparameter set

IV. RESULT

Performance evaluation of the proposed Hybrid QCNN-SOA method for CNC machine bearing fault detection through vibration and acoustic signals takes place in this part. The entire research operated on Python 3.7.14 under the Windows 10 operating system.

Data Description

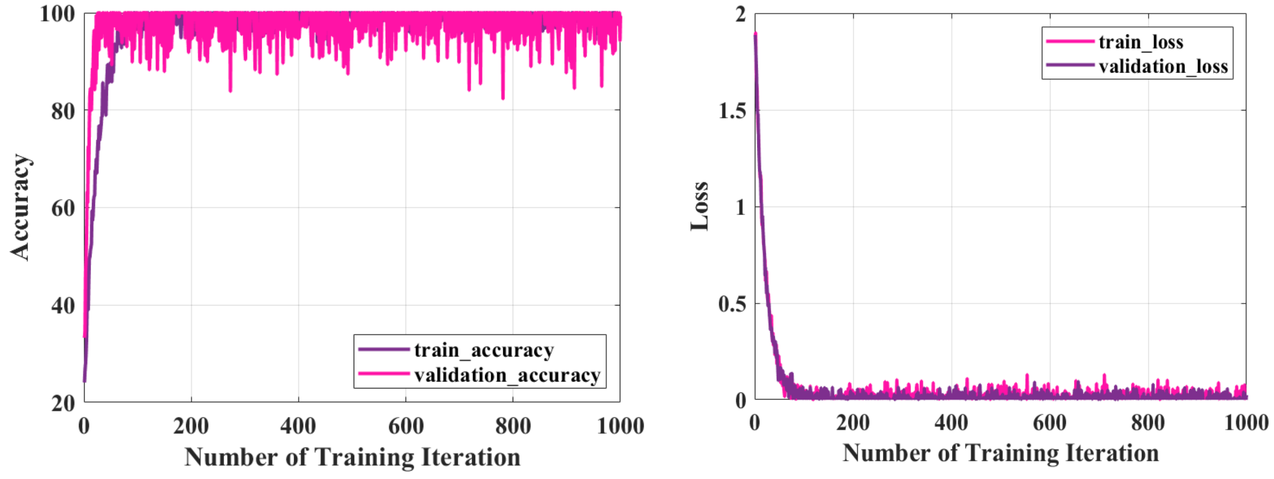
The dataset for this study involves the collection of acceleration signals from a CNC machining center to evaluate bearing health under various operating conditions. The manufacturer used MCL-12 CNC machine equipment which operated its 1.5KW spindle-style AC induction motor at a rate of 2800 rpm. Research took place on the X-axis of the machine through its combination of an AC motor together with ball screw and gearbox and bearings. Two types of accelerometers were utilized: an internal accelerometer that was stationary in the axial direction and revolved together with the planet carrier, and a radial accelerometer that was mounted outward on the outer race. The procedure consisted of performing experiments at 14 Hz shaft speed while changing the torque loading from 30 Nm to 50 Nm to 70 Nm. The research used healthy and two defective bearing states for data collection: inner race and outside race. The following t **Table 1** summarizes the test conditions.

Table 1. Bearing Test Circumstances

Test No.	Load (Nm)	Input Shaft Speed (Hz)
1	30	14
2	30	14
3	30	14
4	50	14
5	50	14
6	50	14
7	70	14
8	70	14
9	70	14

Performance Analysis

The proposed method is assessed and contrasted with a number of current techniques for CNC machine bearing defect detection, including as CNN [9], MSVM [10], AdaBoost [11], and CART [12]. Performance assessment of models happens through several metrics including accuracy and precision and recall alongside F1-score and error rate. A performance evaluation of diagnostic and classification ability for bearing defect detection utilizes vibration and acoustic signals through these metrics.



(a) **(b)**

Fig 2. Proposed (A) Accuracy (B) Loss Graph**.**

The accuracy (a) and loss (b) over training iterations are the two graphs in the provided **Fig 2**. Good model performance is indicated by the accuracy graph, which shows that both training and validation accuracy rise quickly and stabilize between 95 and 100% after about 100 iterations. Both training and validation loss exhibit a sharp reduction in the loss graph, stabilizing close to zero after roughly 200 cycles, indicating successful learning. Nonetheless, the tiny variations in loss and accuracy could be a sign of noise or overfitting. The model is useful for classification jobs since it performs well with little loss. Additional regularization might make stability better.

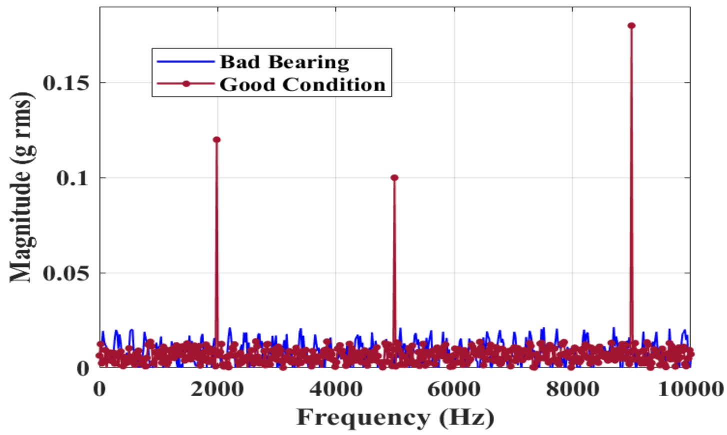


Fig 3. Frequency Spectrum Comparison of Bearing Conditions.

A comparison of the frequency spectrums of a "Bad Bearing" and a "Good Condition" is shown in the **Fig 3**. Magnitude (g rms) is indicated on the y-axis, while frequency (Hz) is represented on the x-axis. Significant peaks with magnitudes of roughly 0.12 g, 0.1 g, and 0.16 g may be seen in the "Good Condition" example at roughly 2000 Hz, 5000 Hz, and 9000 Hz. In contrast, the vibration levels in the "Bad Bearing" instance are lower and more uniformly distributed. The "Good Condition" data indicates resonance at particular frequencies due to the presence of identifiable peaks.

Table 2. Performance Comparison of Different Models for Machine Bearing Fault Detection

Model	Accuracy (%)	Recall (%)	Precision (%)	Error Rate (%)	F1-Score (%)
CNN [9]	98.5	99.2	97.8	1.5	98.5
MSVM [10]	96.4	97.0	94.5	3.6	95.7
AdaBoost [11]	95.1	96.5	92.3	4.9	94.3
CART [12]	92.8	94.0	90.2	7.2	92.1
DBN [24]	90.8	92.5	94.9	1.0	93.7
Proposed Method	99.2	99.6	98.7	0.8	99.1

The performance of some models for vibration and acoustic signal-based CNC machine bearing defect classification is represented in **Table 2**. The CNN [9] delivered an accuracy rate of 98.5% which included precision levels of 97.8% and recall of 99.2% and F1-score of 98.5% and an error rate of 1.5%. The MSVM [10] exhibited slightly lower performance than other models with 96.4% accuracy and 3.6% error rate and precision of 94.5% and 97.0% recall. The accuracy level of AdaBoost [11] reached 95.1% yet CART [12] stood at only 92.8%. The new method exceeded existing models based on accuracy (99.2%) and precision (98.7%), recall (99.6%) and F1-score (99.1%) as well as error rate (0.8%).

V. CONCLUSION

The suggested Hybrid Quantum Convolutional Neural Network with Skill Optimization Algorithm (QCNN-SOA) presents a new method for detecting CNC machine bearing faults using vibration and acoustic signals. Through the combination of quantum convolutional neural networks and the Skill Optimization Algorithm (SOA), the technique improves fault classification accuracy while reducing error. The Sliding Window Variational Outlier-Robust Kalman Filter (SWVO-RKF) is utilized for preprocessing, which efficiently removes noise and outliers without sacrificing key fault-related patterns. Feature extraction is accomplished using the Inception Convolutional Vision Transformer (ICVT), which captures both local and temporal relationships among the signals. The Hybrid QCNN is utilized for the last classification step, with quantum gates applied to signal encoding, convolution, and pooling, and a classical fully connected layer for categorization. The approach operates at outstanding performance of 99.2% accuracy, 99.6% recall, 98.7% precision, and 99.1% F1-score. Although the approach is excellent at fault detection, its computational requirements resulting from quantum operations pose a limitation. Future research will investigate scalability for larger datasets and integration with predictive maintenance frameworks to enable proactive machine monitoring.

CRediT Author Statement

The authors confirm contribution to the paper as follows:

Conceptualization: Nallabariki Praveen Kumar, Swetha G, Lakshmanarao A, Gururaj L Kulkarni, Sreenivasulu Gogula and Koti Reddy M; **Methodology:** Swetha G, Lakshmanarao A, Gururaj L Kulkarni, Sreenivasulu Gogula and Koti Reddy M; **Software:** Nallabariki Praveen Kumar, Swetha G and Lakshmanarao A; **Data Curation:** Gururaj L Kulkarni, Sreenivasulu Gogula and Koti Reddy M; **Writing- Original Draft Preparation:** Nallabariki Praveen Kumar, Swetha G and Lakshmanarao A; **Investigation:** Nallabariki Praveen Kumar, Swetha G and Lakshmanarao A; **Supervision:** Gururaj L Kulkarni, Sreenivasulu Gogula and Koti Reddy M; **Validation:** Nallabariki Praveen Kumar, Swetha G and Lakshmanarao A; **Writing- Reviewing and Editing:** Nallabariki Praveen Kumar, Swetha G, Lakshmanarao A, Gururaj L Kulkarni, Sreenivasulu Gogula and Koti Reddy M; All authors reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests.

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