A HYBRID QUANTUM-CLASSICAL FRAMEWORK FOR IMAGE-BASED SURFACE FINISH ASSESSMENT OF CNC MILLING

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Abstract

This work introduces a Hybrid Quantum Classical Convolutional Neural Network (HQCNN) framework for image-based surface finish assessment in current manufacturing. Traditional inspection methods and classical machine learning techniques struggle with high computation and require large datasets. The proposed HQCNN combines a Variational Quantum Circuit (VQC) with in a Classical Convolutional Neural network (CNN) to leverage quantum entanglement for capturing complex surface patterns and classical layers for stable prediction. Surface images are taken from face milled aluminium 6061 specimens, obtained by classical image processing, followed by encoded into quantum states using VQC and gradients were computed by Parameter Shift Rule (PSR). The proposed hybrid model gives better prediction accuracy and works faster than classical CNNs even with limited data. This shows that using quantum-enhanced learning can make future manufacturing systems smarter and more efficient.

***Keywords*—** HQCNN, Parameter Shift Rule, Surface Roughness, Variational Quantum Circuit.

1. INTRODUCTION

Surface roughness plays a major role in determining the functional performance and fatigue strength of machined components. Accurate inspection of surface finish is required for ensuring product quality and process control in manufacturing units. Traditional roughness measurement techniques are time-consuming and limited to localized inspection areas [1]. Artificial intelligence techniques such as regression models, neural networks, and ensemble methods have been increasingly applied for surface quality prediction due to their ability to learn nonlinear relationships among multiple cutting parameters. Measuring surface roughness values like Ra and Rz is important to maintain quality standards, especially in industries such as aerospace and automotive engineering [2]. Studies introducing multi-sensor data fusion with machine learning algorithms have also shown improvements in prediction accuracy, particularly for ultra-precision milling applications [3].

However, the high computational speed of training deep learning models and the limited analyze ability of large networks remain key challenges. To address these challenges, hybrid quantum-classical learning models are emerging as a promising alternative. Hybrid quantum-classical convolutional neural networks (HQC-CNNs) utilize the representational power of quantum computing while retaining the learning efficiency of classical algorithms. It enables enhanced feature extraction and reduced model complexity [4]. In face milling, surface roughness depends on feed rate, speed, and dynamic factors. Moreover, theoretical and experimental progress in hybrid quantum-classical algorithms has demonstrated their suitability for near-term quantum devices, offering a pathway to practical implementation in manufacturing analytics [5], [6].

2. LITERATURE SURVEY

Several recent studies have explored the integration of hybrid and quantum neural network models for image-based prediction and classification tasks. Bokhan et al. [7] introduced a multi class classification model using Quantum Convolutional Neural Networks (QCNNs) with hybrid quantum-classical machine learning. By demonstrating this to reduce parameter dependency and improve classification efficiency compared to classical deep neural networks. Similarly, Iqbal et al. [8] proposed a hybrid QCNN model for the Iris dataset classification problem, showing enhanced accuracy and generalization performance even with a limited number of samples. Further examined hybrid quantum-classical CNNs for image classification tasks and validated the ability of quantum circuits to improve representational capacity and reduce computational load. Sebastianelli et al. [9] applied circuit-based hybrid quantum neural networks to remote-sensing image classification, emphasizing the adaptability of quantum layers in handling large and complex visual datasets. Sachdeva et al. [10] explored the role of quantum computing in image processing, highlighting how quantum mechanisms such as superposition can accelerate image transformation, compression, and enhancement operations. outlined hybrid quantum-classical algorithms, establishing theoretical frameworks that support the coexistence of classical optimization and quantum computation for scalable machine learning solutions. Yao et al. [12] developed a quantum image processing model capable of performing efficient edge detection, demonstrating the potential of quantum circuits for real- world visual analysis.

3. METHODOLOGY

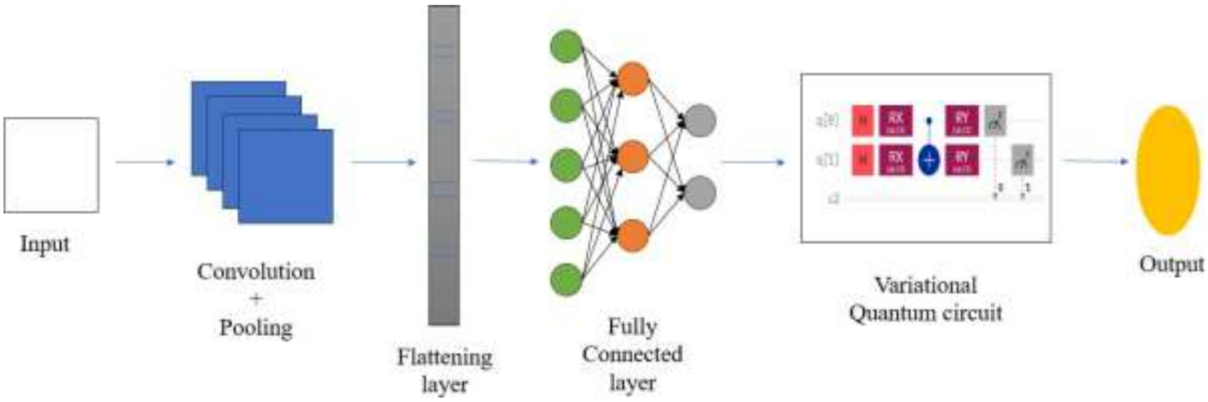

Fig. 1: Hybrid Quantum-Convolutional Neural Network Architecture

Fig.1 Framework combines both classical convolutional operations and quantum learning to evaluate the surface finish of machined components through image processing.

Input layer: Surface images are used as input data, each image is processed through normalization, grayscale conversion & resizing to maintain uniform dimensions.

Convolution + pooling: In convolution, local feature extraction takes place from the input images. Filters are applied to detect spatial patterns (edges, textures and irregularities). It indicates variations in surface roughness. The extracted feature maps represent the initial transformation of raw image data into a structured format suitable for further analysis. Then pooling reduces the spatial dimensionality of the feature maps. This minimizes computational complexity, and prevents overfitting.

Flattening layer: The output which comes from pooling stage is flattened into a one- dimensional feature vector (converts the 2D feature maps into 1D vector because dense can only accept 1D input).

Fully connected layer: That 1D flattened feature passes through one or more dense layers. It combines local feature into a higher-level representation. This stage modifies parameters and improves model ability to classify/ regress surface roughness levels.

Quantum layer: Initially the qubits in |0> state. The output from the classical dense layer is encoded into quantum states using angle encoding. Those inputs are in superposition now, those are parameterized by using quantum gates like Hadamard, rotation gates (RX, RY, RZ) and CNOT (controlled NOT) for entangling operations. These entire operations call it as variational quantum circuit (or) parameterized quantum circuit. The parameters of the circuit are optimized through a hybrid loop. Here the quantum circuit computes expectation values and the classical optimizer updates parameters based on a defined cost function.

Output layer: It is final stage of framework. After processing VQC, the quantum states are measured by Pauli's-Z operator. These measurements produce expectation values, which represents the probabilistic outcomes of Quantum Computation.

Training and optimization: This hybrid model is trained by joint optimization process. In forward pass starts with classical convolution followed by dense and VQC and then predicted output. The main objective of training is to minimize the error between predicted output and target surface roughness.

During back propagation, classical parameters are updated using gradient methods. However, in quantum circuit parameters, gradients cannot be directly computed through classical differentiation. To overcome this PSR is used (Parameter Shift Rule). It estimates the gradient of expectation value of each quantum gate parameter by executing the circuit twice. (once with a positive phase shift and once with a negative shift of 90°). This hybrid training loop continuous iteratively till it predicts accurately.

4. EXPERIMENTATION

Fig. 2: JV 55 model CNC machine

Fig. 3: Aluminium 6061 bars

Fig. 2 shows the CNC face milling setup used in this study. The JV 55 CNC machine was used to perform the milling operation on aluminium workpieces. It is a high-precision machine with adjustable spindle speed and feed rate, suitable for medium-sized components

Fig. 3 represents the Aluminium 6061 workpieces used for the face milling operation. This material was chosen for its high strength, good machinability, corrosion resistance, and excellent surface finish quality. Rectangular bars of size 245 × 110 × 15 mm were used as samples in the study.

The following were the input parameters for the Milling process, speed varies greatly depending on work piece material composition, speed, feed, tool material, tool design, and cutting fluid. Table 1 shows that the range of speed, feed, depth of cut used in this experimentation.

Table. 1: Range of input parameters for milling.

Parameter	Units	Range
Spindle Speed	RPM	1200-1400
Feed	mm/min	400-800
Depth Of Cut	mm	1.5-2.5

Fig. 4: Measurement of surface roughness using Talysurf tester

Fig.4 shows the experimental measurement of surface roughness for the machined Aluminium 6061 workpieces using a Talysurf surface roughness tester. The instrument provides high- precision surface topography readings in micrometers (µm), enabling accurate evaluation of machining quality. Each sample was positioned under the stylus probe to obtain average roughness values for further analysis and correlation with machining parameters.

Fig 5: Surface roughness image dataset [13]

Fig. 5 represents the surface roughness image dataset used in this study. It consists of multiple face-milled Aluminium 6061 specimens exhibiting a wide range of surface texture variations. Each image represents a unique combination of machining parameters such as spindle speed, feed rate, and depth of cut, resulting in distinct surface finish characteristics. These images were obtained from a publicly available online dataset [13].

Table 2 presents the machining parameters and the corresponding experimental surface roughness (Ra) values. After face milling, 27 surface roughness values were recorded using a Talysurf instrument. For each condition, three trials were conducted, and the final surface roughness value was obtained by taking the average of the three readings [14].

Table. 2: Experimental dataset

S. No	**Speed (RPM)**	**Feed (mm/min)**	**th of cut (mm)**	**xperimental surface roughness Ra (μm)**
1	1200	400	1.5	2.759
2	1200	400	2	2.943
3	1200	400	2.5	3.225
4	1200	600	1.5	3.469
5	1200	600	2	3.689
6	1200	600	2.5	4.069
7	1200	800	1.5	4.135
8	1200	800	2	4.281
9	1200	800	2.5	4.485
10	1300	400	1.5	2.652
11	1300	400	2	2.901
12	1300	400	2.5	3.125
13	1300	600	1.5	3.964
14	1300	600	2	3.628
15	1300	600	2.5	4.019
16	1300	800	1.5	4.198
17	1300	800	2	4.256
18	1300	800	2.5	4.356
19	1400	400	1.5	2.579
20	1400	400	2	2.894
21	1400	400	2.5	3.012
22	1400	600	1.5	3.349
23	1400	600	2	3.569
24	1400	600	2.5	3.989
25	1400	800	1.5	3.918
26	1400	800	2	4.259
27	1400	800	2.5	4.218

The convolutional neural network (CNN) model was trained using 25 images and tested with 2 unseen images. Each image was labelled with its corresponding experimentally measured surface roughness (Ra) value, which was normalized between 0 and 1. The CNN converts

RGB images into grayscale images of size 64 × 64 pixels. The model consists of 9 layers, including three convolutional layers with 16, 32, and 64 filters, each followed by a 2×2 max pooling layer, and three fully connected layers with 128, 64, and 1 neuron, respectively. The ReLU (Rectified Linear Unit) activation function was used in the hidden layers. The model was trained for 30 epochs using the Adam optimizer with a learning rate of 0.0005 and mean squared error (MSE) as the loss function.

For the Hybrid Quantum Convolutional Neural Network (HQCNN), the model was implemented in Google Colab after installing IBM Qiskit and Qiskit Machine Learning libraries. The image dataset was divided into training, testing, and validation sets, with each image labeled by its experimental surface roughness value. The HQCNN includes two convolutional layers with ReLU activation, each followed by a max pooling layer to reduce spatial dimensions, and one fully connected layer. A quantum layer was added after the fullyconnected layer, simulated using four qubits and two repetitions. The quantum circuit employs RY and RZ rotation gates along with CNOT gates for entanglement. The HQCNN model was trained for 200 epochs using the Adam optimizer with a learning rate of 0.0006 and MSE as the loss function.

5. RESULTS AND DISCUSSIONS

Table 3 presents a comparative analysis of surface roughness prediction results obtained using conventional Convolutional Neural Network (CNN) and Hybrid Quantum-Classical Convolutional Neural Network (HQCNN) models for 25 test samples. From the results, it is clearly identified that the proposed HQCNN demonstrates consistently lower prediction errors compared to the conventional CNN for most samples.

Table. 3: Comparison of results (in µm)

Sample	Exp Ra	CNN	HQCNN	CNN Error	HQCNN Error
1	2.759	3.0891	2.81	0.3301	0.051
2	2.943	2.9177	2.9714	0.0253	0.0284
3	3.225	3.7052	3.6094	0.4802	0.3844
4	3.469	3.6804	3.4785	0.2114	0.0095
5	3.689	3.6557	3.6171	0.0333	0.0719
6	4.069	3.6585	4.0918	0.4105	0.0228
7	4.135	3.6349	4.1012	0.5001	0.0338
8	4.281	3.8427	4.0819	0.4383	0.1991
9	4.485	3.8153	4.3361	0.6697	0.1489
10	2.652	3.7735	2.8005	1.1215	0.1485
11	2.901	3.8076	2.9752	0.9066	0.0742
12	3.125	3.5637	3.111	0.4387	0.014
13	3.964	3.8661	3.6328	0.0979	0.3312
14	3.628	3.6767	3.6297	0.0487	0.0017
15	4.019	3.4425	4.0067	0.5765	0.0123
16	4.198	3.4411	4.2314	0.7569	0.0334
17	4.256	3.8325	4.2339	0.4235	0.0221
18	4.356	3.4662	4.3089	0.8898	0.0471
19	2.579	3.6343	2.4952	1.0553	0.0838
20	2.894	3.332	2.8781	0.438	0.0159
21	3.012	3.3934	3.0074	0.3814	0.0046

22	3.349	3.8	3.3998	0.451	0.0508
23	3.569	3.757	3.4834	0.188	0.0856
24	3.989	3.645	3.9802	0.344	0.0088
25	3.918	3.3876	3.8776	0.5304	0.0404

Table 4 compares the CNN and HQCNN models with experimental surface roughness. In Sample 1, the experimental Ra value of 4.259 µm was predicted as 3.6169 µm by the CNN and 3.4824 µm by the HQCNN, yielding errors of 0.6421 µm and 0.7766 µm respectively. In Sample 2 demonstrates better alignment with the experimental value, where the HQCNN achieved a lower error (0.4763 µm) compared to the CNN (0.732 µm). Overall, the results confirm that the HQCNN effectively generalizes to previously unseen surface texture patterns, maintaining competitive accuracy without overfitting.

Table. 4: New samples Prediction in µm

Sample	Exp Ra	CNN	HQCNN	CNN Error	HQCNN Error
1	4.259	3.6169	3.4824	0.6421	0.7766
2	4.218	3.4860	3.7417	0.732	0.4763

Table 5 presents a comparison based on 27 surface images of face-milled Aluminium 6061 specimens. On that 25 used for training and 2 are unseen new images. By this the results clearly indicates that HQCNN is better compare to CNN in all error metrics. The HQCNN achieved a Mean Absolute Error (MAE) of 0.0770 and 0.6265 µm in both seen and unseen patterns. Whereas in CNN achieved MAE of 0.4699 and 0.6871 µm.

Table. 5: Comparison of Errors

Metric	25 samples CNN	25 samples HQCNN	New samples CNN	New samples HQCNN
MAE	0.4699	0.0770	0.6871	0.6265
MSE	0.3077	0.0152	0.4761	0.4117
RMSE	0.5546	0.1233	0.6899	0.6416

(**MAE**- Mean Absolute Error, **MSE**- Mean Squared Error, **RMSE**- Root Mean Squared Error).

6. CONCLUSION

This research introduced a hybrid quantum-classical convolutional neural network (HQCNN) for analysing the surface finish of face-milled aluminium components through image processing. The proposed framework successfully integrates classical convolutional operations with quantum variational circuits to enhance feature learning and pattern recognition. Thehybrid model was trained using limited experimental data. From the prediction results confirmed that the HQCNN consistently achieved lower prediction errors compared to a conventional CNN. although the dataset is too small HQCNN predicts accurately compare to alone CNN. By the Integration of quantum computing into manufacturing industries can improves defect detection and quality assessment processes.

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