Quantum machine learning ensemble for surface crack detection

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ABSTRACT

By identifying the aspects of manual inspection methods in the context of industrial production, which are described within the undertaken research, the development of an automated visual inspection technology is driven. This causes more time to be spent on performing the checks, thus adding to the labor cost. The efficiency of the operations is reduced, and there is a tendency for errors due to fatigue in checking 24/7. The proposed solution for a new product is designed to change the approach of the existing manufacturing process by using the automated system to self-inspect the surface and notify of its defects during manufacturing. As an enhancing advancement, this new development aims to address apprehensions pertaining to manual examination as the world transitions into the fault-tolerant period. Lastly, this approach fits the universal grail of further developing industrial capacities, with the resulting thought process extending to the incorporation of technologies such as quantum computing with the current requirements of manufacturing. Other potential applications of this approach, including aerospace applications of ultrasonic testing or thermography in the detection of surface cracks, might also help improve this approach in the future.

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1. INTRODUCTION

This study maps the perspective of quantum convolutional neural networks (QCNNs), with emphasis on the extension of hybrid methods in order to deal with the problems inherent to the present NISQ epoch. Inherent to the abstracts are two quantum components: a quantum sliding window layer and a quantum simple layer. SurfNetv2 belongs to the QSurfNet model, which is based on both VGG and residual net structures, and utilizes the quantum sliding window layer with classical components [1]. It can be argued that this strategic integration is designed to leverage the strengths of both quantum and classical paradigms. The study focuses on quantum convolutional layers in detail, with a focus on quantum sliding window and quantum convolutional (quanvolutional) layers. For example, when the parameters of quanvolutional layers are randomly selected, the model is less effective compared to having trainable quanvolutional layers. This distinction becomes useful to improve the quantum layers for feature extraction. This approach involves integrating quantum layers with other typical convolutional networks, including VGG16 and ResNet [2], [3].

The addition of a quantum simple layer is deemed to be an effective improvement, which can be confirmed to have improved the classification of images.

2. PROPOSED METHOD

A proposed method to improve surface crack detection using quantum computing principles and quantum machine learning involves integrating the two paradigms of computational thinking for better performance. To be more precise, this hybrid approach combines the part of quantum-feature space representation with the usage of the enhanced feature maps, which means that the classical datasets are mapped to the quantum states [4]-[10]. In this paper, quantum neural networks (QNN) are used to incorporate the feature of quantum parallelism so as to optimize the parameter-setting of the model for identifying elaborate patterns in crack images [11]-[15]. Moreover, specific quantum algorithms, like quantum support vector machines, are used to take advantage of the quantum computational complexity. Challenges such as quantum error correction and decoherence are also considered in the proposed model using a blend of classical error correction and state-of-the-art quantum algorithms. In comparing this model, one needs to compare it with such classical methods of machine learning that are used for the detection of surface cracks. This quantum-classical coupled paradigm suggests the possibility for advancing the state of the art in surface crack detection, giving a preview of what the future of quantum machine learning based methods might entail in this scenario [16]-[22].

As you can see in Figure 1, there are three binary models, and the classes are Yes/No:

- Quantum simple convolution layer with the transfer learning (QSCL-TL)
- Quantum sliding window with QSurfNet (QSW-QSurf)
- Quantum support vector machine with transfer learning (QSVM-TL)

For the TL architecture, refer to Figure 1, which shows models to classify whether a certain image has a literal crack on it or not. Moreover, there are two more models that classify the type of the crack, the classes are crazing, inclusion, patches, pitted-surface, rolled-in scale, and scratches: QSCL-TL (multi-class model) and QSVM-TL (multi-class model). As not all cracks are a literal crack, a detailed explanation for this architecture and observation can be found in the general observation section of this paper. This is an ensemble approach where each model is weighted according to its accuracy [23].

Figure 1. Proposed system method

3. METHOD

The quantum sliding window layer comprises two main components: i) The first model, which either uses for feature extraction VGG16 or ResNet5 pre-trained models; and ii) The second model under investigation is the model that involves a QCNN combined with a dense layer. The three different QCNN models include QCNN simple, QCNN sliding, and the quanvolutional layer.

3.1. Angle embedding

To embed classical inputs into quantum states, you use an angle embedding technique. The embedding gate with rotation along the Y-axis for a given qubit i with input is as (1).

$$R_y(X_i) = (cos(X_i/2)\ -sin(X_i/2)\ sin(X_i/2)\ cos(X_i/2)\ ) \tag{1}$$

By applying this rotation gate to the qubit, we effectively encode the classical input $\boldsymbol{Xi}$. into a quantum state, allowing quantum operations to be performed on it. This technique is often used as part of quantum algorithms and quantum machine learning models for processing classical data in a quantum framework.

3.2. Entanglement with CNOT gates

The controlled-NOT (CNOT) gate between two qubits, j and s defined as (2).

$$R_{rotation}(W) = (cos(W/2)\ -sin(W/2)\ sin(W/2)\ cos(W/2)\ ) \quad (2)$$

The matrix you provided seems to be a specific instance of the CNOT gate acting on qubits where$j$ is some arbitrary qubit index. The structure of the matrix remains the same, but its position within a larger quantum circuit might vary, hence the subscript notation (j, j + 1) (j, j + 1) to denote the specific qubits it operates on [24], [25].

3.3. Layered structure with rotations

Within each layer, the following sequence of operations is applied: rotation gates are applied to each qubit using parameters w. Each layer of the quantum convolutional neural network (QCNN) follows a systematic sequence of operations designed to transform and entangle the input quantum states. The process begins with the application of parameterized single-qubit rotation gates, which are driven by learnable weight parameters and allow each qubit to traverse a more expressive subspace of the Hilbert space. After these local transformations, entanglement is introduced between adjacent qubits using controlled-NOT (CNOT) gates. In (3) presents the standard CNOT gate is presented as a flattened 1D vector in row-major order, where the gate conditionally flips the target qubit $(\mathrm{j}+1)$ based on the state of the control qubit j.

$$CNOT_{j,j+1} = (1\ 0\ 0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ ) \quad (3)$$

This gate structure preserves the control qubit and introduces a NOT operation on the target qubit only when the control qubit is in the$|\ 1\rangle$ state, thereby enabling quantum entanglement. The repeated application of such rotation and entanglement blocks across multiple layers allows the QCNN to capture complex feature relationships in the quantum domain, making it a powerful architecture for quantum-enhanced learning tasks.

4. RESULTS AND DISCUSSION

In the quanvolutional layers used as a pre-processing stage, there are encoding and decoding mechanisms at play, with different levels of effectiveness. When moving to quanvolutional simple convolution layers, a noticeable decline in model accuracy is observed compared to classical ones. This decrease in performance is not due to the image size but rather due to the challenges posed by quantum simple convolution layers, especially when working with low-quality images. Compared to the proposal of processing the image as a whole, this method holds potential for dealing efficiently with high-resolution images and extracting features in a more complex manner, implying the possible usage of the proposed layer in quantum models of quantum neural networks. Used a pre-processing technique that acts as a preparatory step before the regular pre-processing; all the images were first input to the quanvolutional layer and then to the regular model. Benchmarking has been done on quantum-processed data against the data without any processing. Encoding 1 - Angle encoding: Use Ry gates and decoding counts the number of “1” in the most probable states, refer to Figures 2-4.

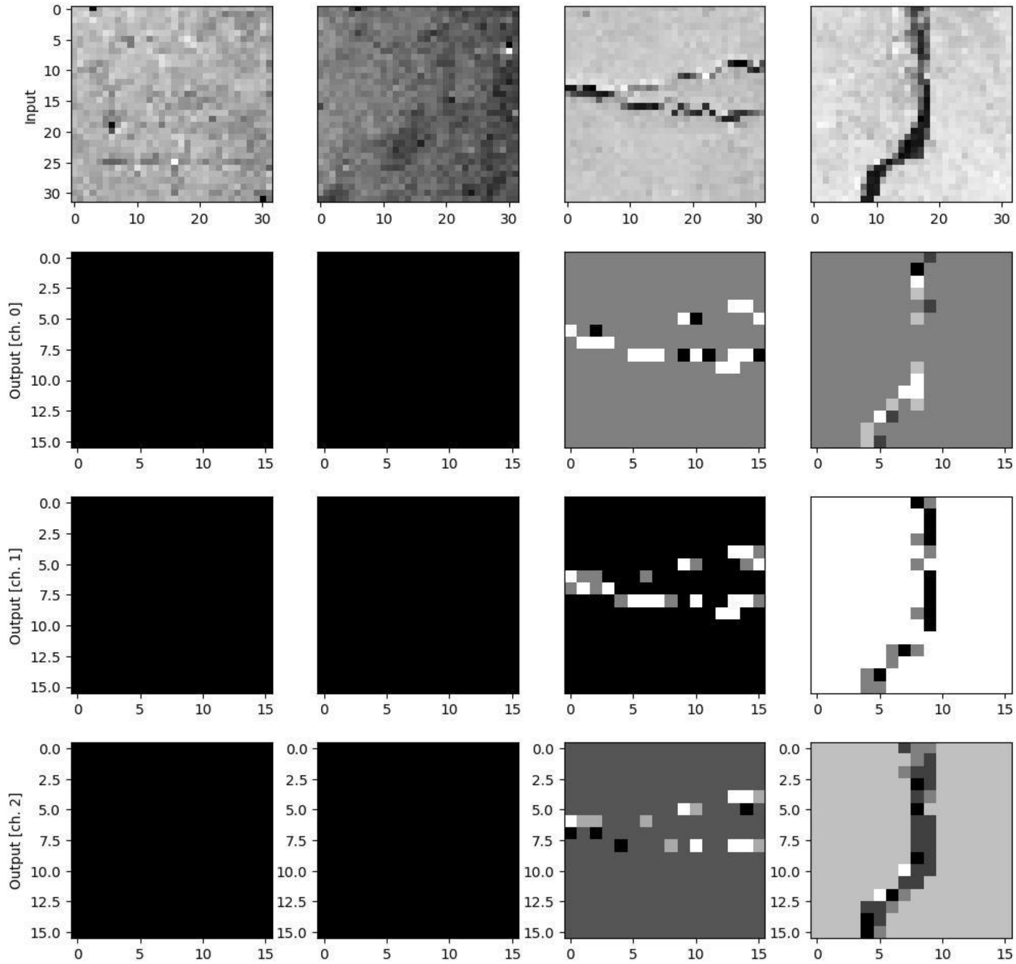
Quantum simple convolution layer-this layer is merely a PQC that passes the output from the previous classical layer, and the output of this is passed onto the next quantum layer, refer to Figure 5. Quantum NN – 1 QCNN layer with 1CNN layer and 2 dense layers. No of filters = 1(first layer) and 8(2nd layer). CNN - 2 CNN layers and 2 dense layers. No of filters = 1(first layer) and 16(2nd layer). Filter size for all convolution layers = 2×2. All the experiments have been conducted thrice, and the average is taken so that one can take into account a more generalization, as shown in Figures 6 and 7.

Observing the results that are available in Table 1 above, it will be noted that training the model using the quantum sliding window layer helps particularly in the case where the layer serves as the selecting feature. However, influencing training accuracy and slightly less capability in generalization, the quantum model is slightly inferior to the classical model. The same trend, similar to the one observed in accuracy, is also seen for recall, where we get a slight hint of overfitting. Although it is merely a guess, it is likely that including a quantum sliding window layer at the start of the model is helpful for the model.

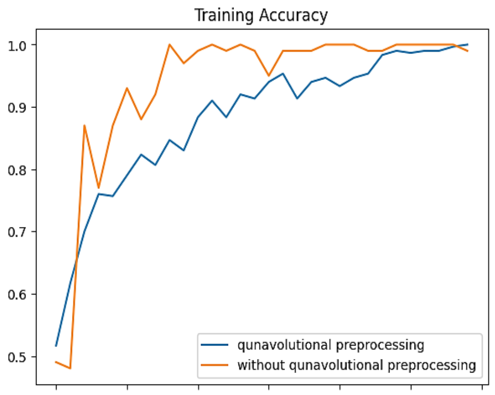
Table 1. Precision and accuracy for PQC 1 and PQC 2 for different setups

Model	Accuracy train	Accuracy test	Precision train	Precision test	Recall train	Recall test	Parameters
QCNN PQC 1	0.899	0.633	0.886	0.777	0.886	0.437	6149
QCNN PQC 2	0.9	0.622	0.886	0.768	0.886	0.411	6149
CNN	0.874	0.773	0.758	0.759	0.754	0.612	7826
CNN + Quanvolutional	0.606	0.566	0.633	0.666	0.133	0.133	7826

(a)



(b)



(c)

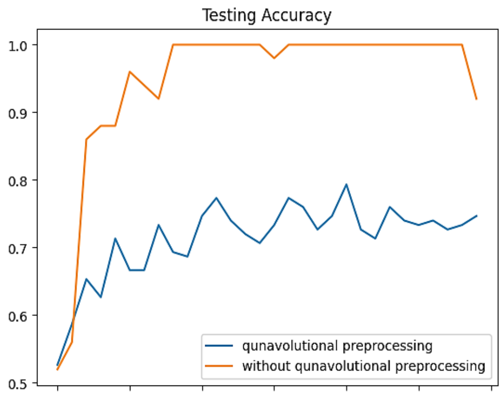
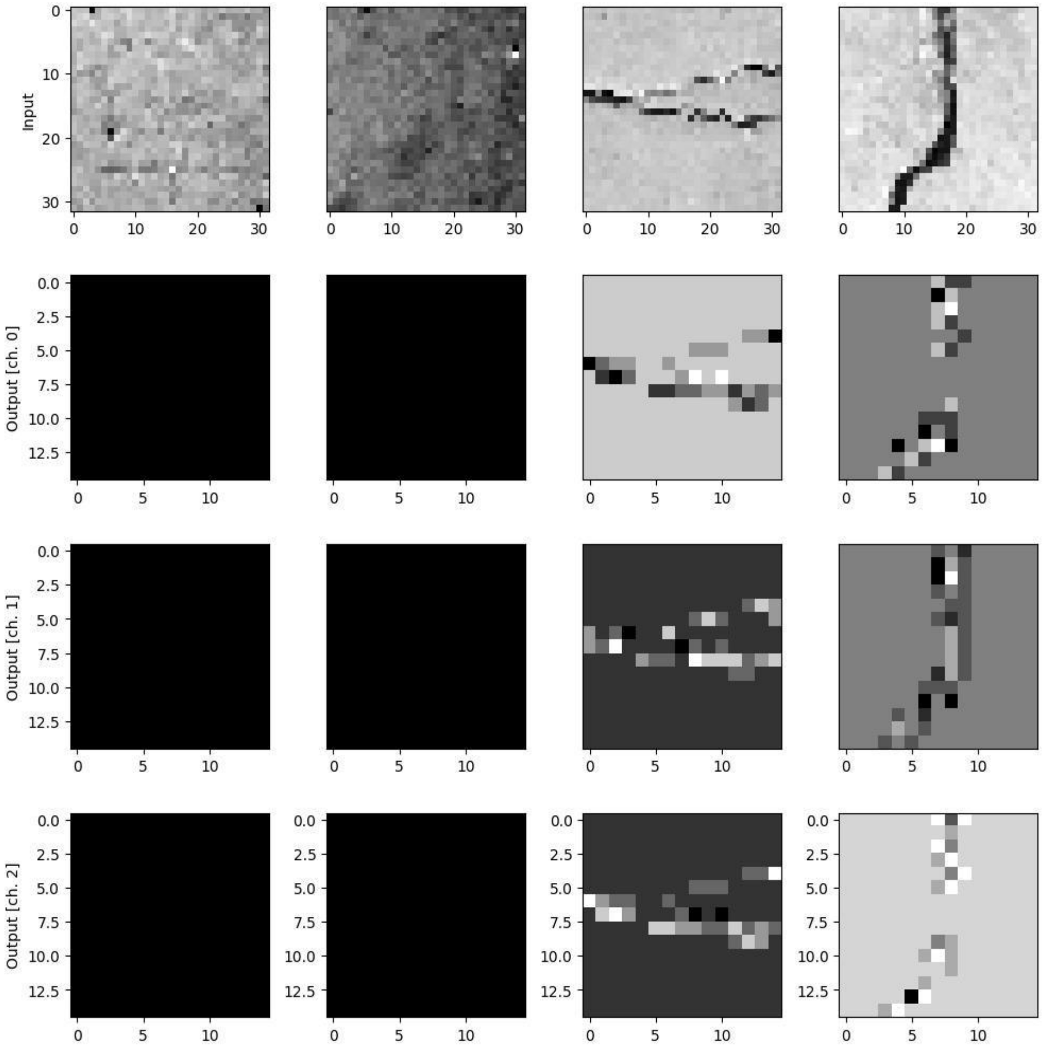
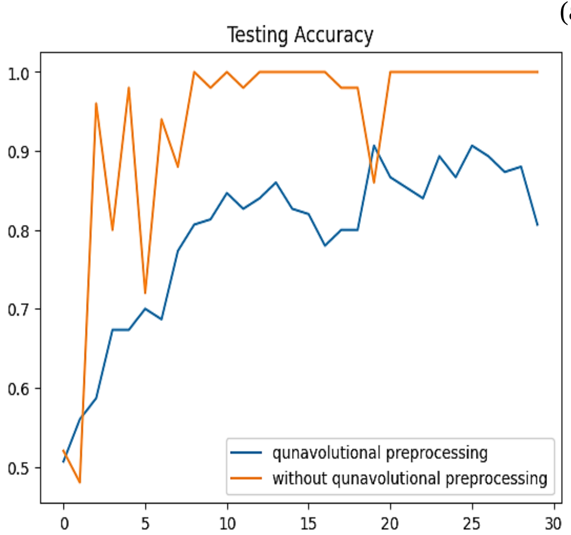


Figure 2. Evaluation of the quanvolutional layers angle encoding 1: (a) feature representations, (b) training accuracy comparison, and (c) testing accuracy comparison

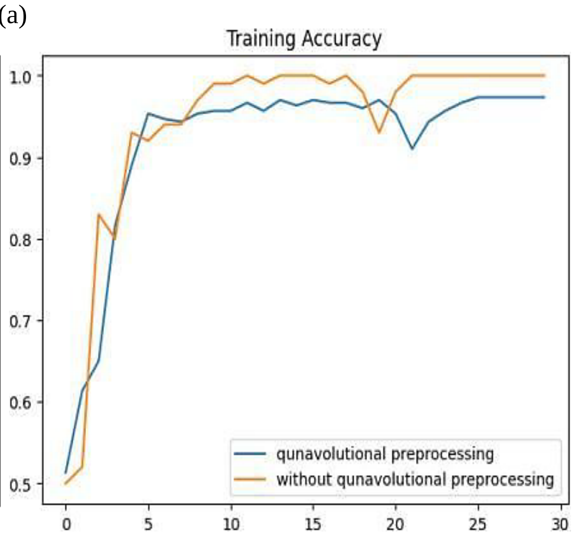
Observed that the simple layer QCNN is able to benefit the model. This is similar to the architecture used by the PennyLane tutorial. Hence, quantum transfer learning (QTL) with a simple convolution layer is beneficial. Quantum simple convolution layers function similarly to the classical dense layer and not the convolution layer as claimed earlier; actually, they perform poorly when it is used only in simple layers of the QTL scenario. When used at the beginning of the NN, it does not work well enough. Another layer, namely the quantum sliding window layer, which is analogous to the normal classical layer is capable of works well whenever feature extraction is to be applied, i. e when the layer is used at the front end of the NN. Quantum sliding window can therefore be a plus in models such as QSurfNet where it is employed at the onset, and a simple convolution layer operates in harmony with QTL in a similar way as a standard dense layer would.



(a)

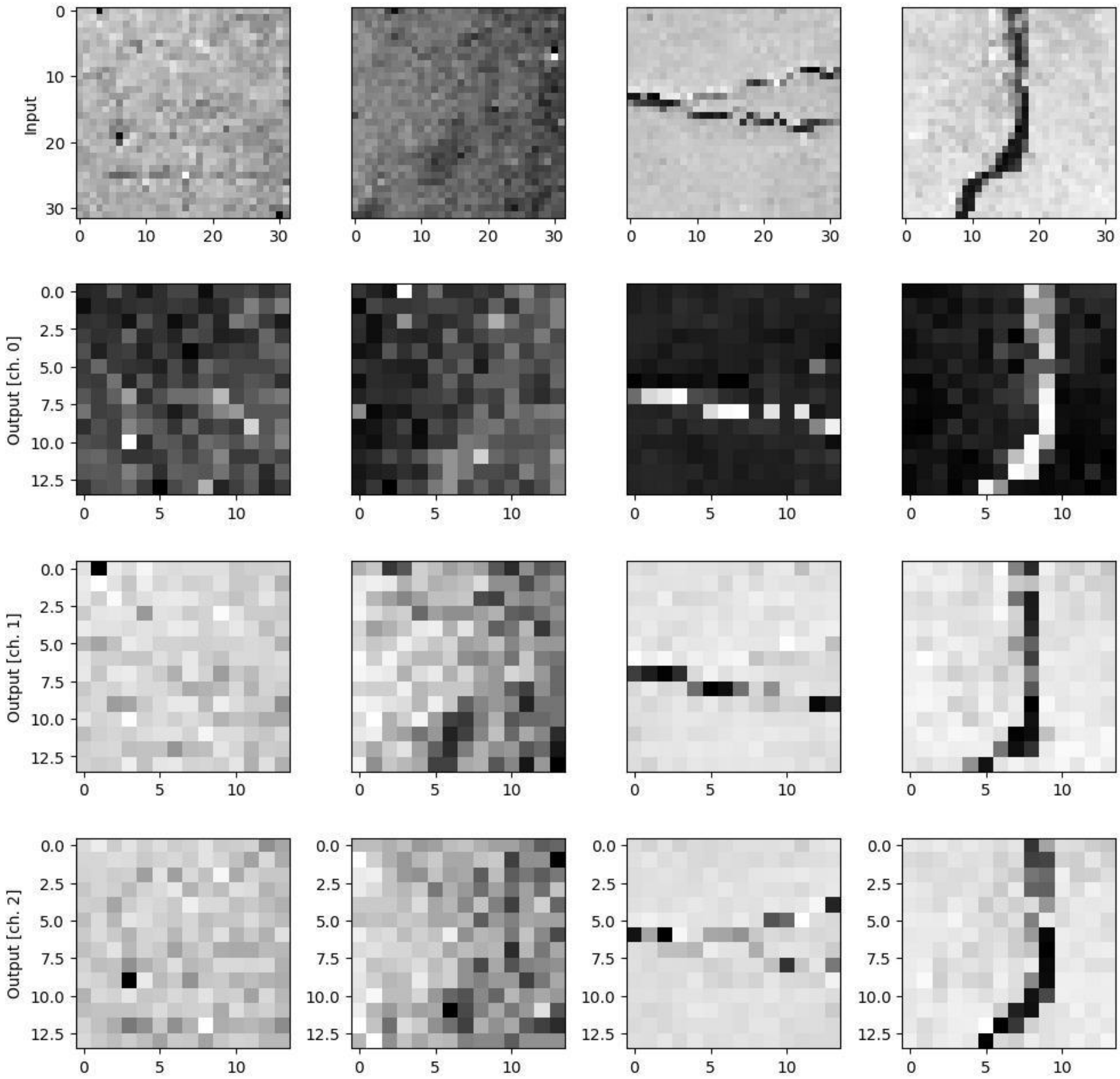


(b)

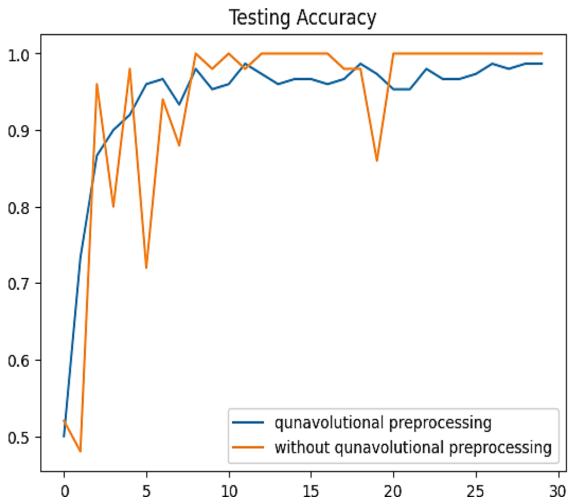


(c)

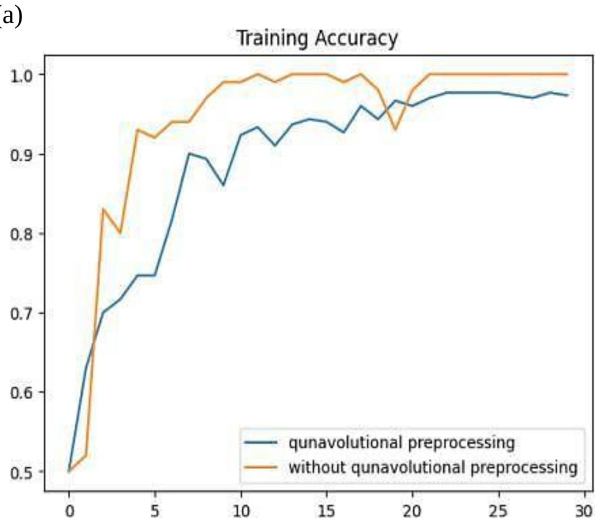
Figure 3. Evaluation of the quanvolutional layers angle encoding 2: (a) feature representations, (b) training accuracy comparison, and (c) testing accuracy comparison



(a)



(b)



(c)

Figure 4. Evaluation of the quanvolutional layers threshold: (a) feature representations, (b) training accuracy comparison, and (c) testing accuracy comparison

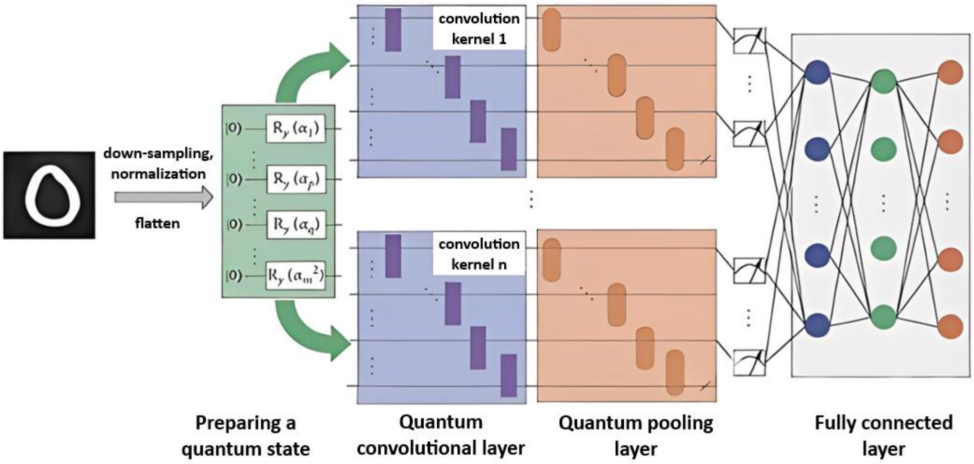


Figure 5. Quantum simple convolution layer

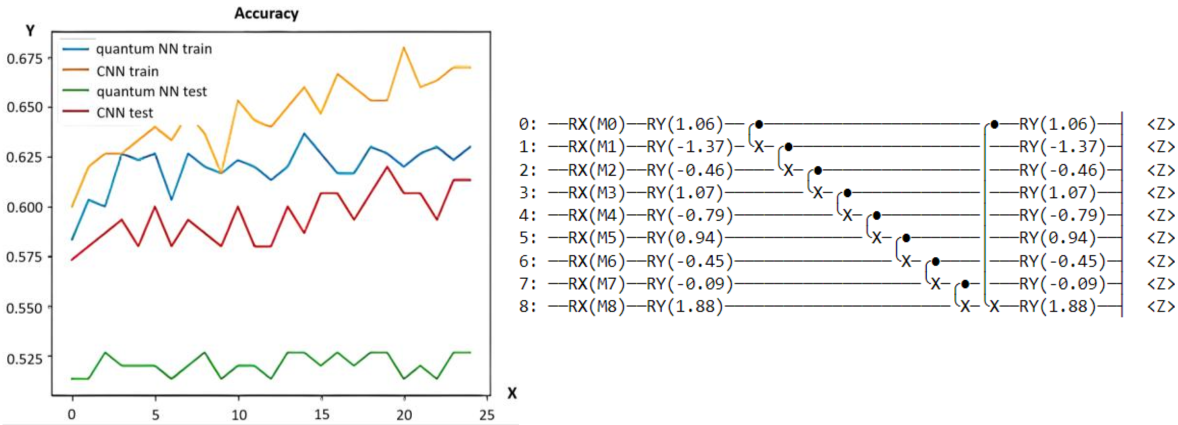


Figure 6. Quantum NN accuracy and circuit

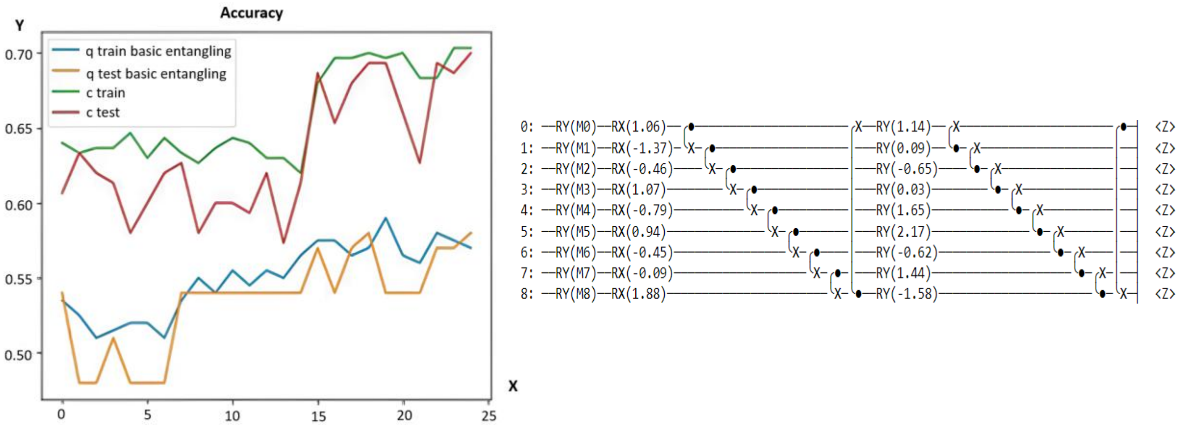


Figure 7. Basic entangling accuracy and circuit

5. CONCLUSION

The usability of quantum technologies in advancing industrial production through visual automation has been showcased on this study. To do this, the study uses the QCNNs and HYNN approaches that counter some of the challenges associated with traditional manual inspection and which include high operating costs due to high labor costs, inefficiencies, and possible human errors during continuous operations. By incorporating classical senses into quantum characteristics this approach was developed to revolutionize the world of production, especially with relation to defect identification. Here, the research findings indicate that DQL with quantum sliding window layers and quantum simple layers offer an immense improvement compared to analogous purely classical ones. The enhancement of quantum transfer learning (QTL) in the hybrid architectures is also seem to be a promising direction for improvement of image classification outcomes due to the contribution of convolutional networks and quantum features. Quantum archetypes of convolutional neural networks such as VGG16 and ResNet, quantum convolutional layers, are integrated into constructing deeper quantum SurfNet (QSurfNet) model towards realization of a more accurate and faster fault detection system. This kind of visual inspection actually is half manual and half automatic and it predetermines a further development of manufacturing without tolerant defects.

In total, it can be concluded that the outcomes are in line with the vision of the integration of QT with modern manufacturing trends as a means of increasing productivity and reliability of the QC processes along with the greater adoption of automation. These could have broader significance, assuming not just the industrial manufacturing application, but also in other undertakings such as aerospace where complex use of ultrasonic testing as well as thermograph are vital. Future works will advance these hybrid structures and investigate further quantum components, as well as disseminating the use of this technology into other domains of industries and engineering. It might take some time to achieve full-scale integration of quantum functionalities in manufacturing; however, key development steps are being made to create the foundations for a new world of automated visual inspection. All source codes and datasets are publicly available at https://gitfront.io/r/dhamotharan/5wyfPqRsNEw3/Quantum-Sruface-Crack-Detection/.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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