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Hybrid Quantum Convolutional Neural Network for Photovoltaic Defect Classification Using Electroluminescence Images

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ABSTRACT

As photovoltaic (PV) systems become more widespread, they need inspection methods that are both reliable and automated. Near-infrared electroluminescence imaging can reveal internal cell defects that visual inspection may miss. Many conventional CNN-based classifiers, however, use deep backbones with large numbers of trainable parameters and often require substantial labelled datasets. This has encouraged interest in more compact hybrid architectures. Here, we evaluate a Hybrid Quantum Convolutional Neural Network for classifying PV defects in electroluminescence images. The model replaces the first convolutional stage of a classical CNN with a quantum convolutional layer based on angle encoding, cyclic entanglement, parameterized rotations and Pauli-Z measurement. We tested it on a five-class subset of 409 images from the PVEL-AD dataset and compared it with CNN-based models including ResNet, DenseNet, GoogLeNet, AlexNet and CNN-LSTM. The subset was chosen to keep quantum-circuit simulation computationally manageable. With approximately 35K trainable parameters, the Hybrid QCNN reached 75.8% accuracy in this feasibility experiment. It used far fewer parameters than several classical models, but its deployment is constrained by the latency introduced by quantum-circuit simulation. The results support the feasibility of the approach, while further work is needed before it can support real-time monitoring.

1. Introduction

As photovoltaic (PV) systems become more widespread, they need inspection methods that are both reliable and automated. Near-infrared electroluminescence imaging can reveal internal cell defects that visual inspection may miss. However, they are time-consuming and may fail to detect subtle defects [1]. On the other hand, electrical testing may fail to identify the exact location of a defect. Therefore, automated PV health monitoring systems have been introduced to improve the accuracy of PV module inspection. Electroluminescence (EL) imaging allows internal solar cell defects to be examined directly. It can detect microcracks, finger interruptions, black regions, short circuits and other structural abnormalities that are difficult to detect manually [2, 3, 4].

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Research shows that many deep learning models for EL imaging have been proposed. EL imaging produces high-resolution images that can capture cell-level defects. Deep learning models, especially convolutional neural networks (CNNs), have been used to detect PV defects from EL images as they can effectively learn significant features. For instance, CNN-based models have been applied to the classification and detection of multiple defects such as cracks, finger interruptions, inactive regions and other defect patterns visible in EL imagery [5, 6]. Review articles show that image-based PV defect classification has progressed from conventional CNN pipelines to transfer learning and deeper backbone architectures such as AlexNet, ResNet, GoogLeNet and DenseNet [3, 7, 8].

Despite their effectiveness, many classical deep learning models still depend on relatively large labeled datasets and large numbers of trainable parameters. The PVEL-AD dataset provides a valuable benchmark for investigating classification models for photovoltaic cell defect detection. This dataset has 36,543 near-infrared EL images with normal and abnormal samples for several defect types [9]. These images contain heterogeneous backgrounds and subtle defects that make feature extraction difficult. Therefore, the PVEL-AD dataset is useful for benchmarking performance and evaluating robustness, efficiency and sensitivity to individual classes. QCNNs provide an alternative by incorporating quantum operations into the learning process.

QCNN-based models use quantum encoding, entanglement, parameterized rotations and measurement to generate feature representations. In hybrid quantum–classical architectures, quantum layers can be combined with classical neural network components, providing an alternative approach to image classification. Quantum feature maps can represent inputs in a high-dimensional Hilbert space, although this does not by itself establish a representational or performance advantage over classical models [10, 11]. Their suitability for PV EL defect classification therefore requires task-specific evaluation.

Hybrid quantum architectures have been investigated as an alternative for learning nonlinear feature representations [12]. Depending on the architecture, shared circuit parameters may support a compact model, which motivates their evaluation on limited PV EL datasets. However, a smaller parameter count alone does not establish reduced overfitting or superior classification performance. Local quantum operations provide a different feature extraction mechanism, but their ability to capture useful PV defect patterns must be assessed experimentally. Circuit design and depth may also influence trainability, as explored in other image-based applications [13]. These considerations motivate the present feasibility study without assuming an advantage over classical CNNs.

Previous EL-based PV defect studies have used hybrid classical pipelines, for example, fused deep features from Inception-V3 and ResNet50 followed by a conventional classifier [14] rather than a quantum-classical model. In contrast, hybrid quantum-classical convolutional networks for image classification have been evaluated on generic benchmark images: Liu et al. [15] proposed QCCNNs with quantum-enhanced feature mapping and tested them on Tetris, while Li et al. [16] implemented a parameterized quantum convolution and pooling architecture followed by a classical fully connected layer on MNIST. Liu et al. [17] demonstrate that classical deep learning approaches dominate EL-based PV defect classification, while the comprehensive review by Masita et al. [7] does not address quantum computing approaches. Therefore, these studies establish an architectural precedent, but do not demonstrate its application to EL imaging or PV defect classification. Accordingly, the contribution of the present study is the feasibility evaluation of a hybrid QCNN for classifying PV cell defects from near-infrared EL images.

The proposed model incorporates a quantum convolutional layer into a classical CNN architecture and is evaluated using a subset of the PVEL-AD dataset consisting of five types of defects. Its performance is compared with established deep learning models including CNN, ResNet, DenseNet, GoogLeNet, AlexNet and CNN-LSTM under a six-epoch training setting. This paper

provides a comparative evaluation of the Hybrid QCNN for PV defect classification based on classification performance, parameter efficiency and the potential of hybrid quantum-classical learning for compact solar cell defect detection.

2. Literature Review

2.1 Classical PV-EL Analysis

Photovoltaic (PV) technology uses semiconductor materials to convert sunlight directly into electrical power. It operates through solar cells that are typically made of silicon to produce usable power [18]. Common PV cell technologies include monocrystalline silicon, polycrystalline silicon and thin films. These PV modules can be affected by various defects that can significantly affect their performance and efficiency without proper monitoring and management. Examples of defects include microcracks, delamination, soiling, hotspots, shading effects and overall degradation. Microcracks are small fractures that may not be seen on the surface. They are caused by mechanical stress, thermal cycling or poor installation. They can reduce efficiency or even cause failure.

Delamination is the separation of layers within the module. It can weaken the structure and increase the risk of short circuits [19]. Soiling is caused by dust and debris accumulation. It can reduce sunlight absorption especially in dry environments which may lead to power loss [20]. Damage or uneven sunlight exposure can cause localized overheating, producing hotspots in a panel. Hotspots can cause long-term damage. Shading from nearby objects also can reduce power efficiency [21]. All PV modules experience gradual degradation over prolonged use due to environmental conditions and material limitations. It is shown that the degradation rates typically range from 0.5% to 1% per year and lead to reduced efficiency and power generation. Therefore, continuous monitoring and maintenance are essential to maintain system performance and the lifespan of PV modules [20].

Conventional PV monitoring relies on human inspection. During an inspection, technicians look for cracks, discoloration and dirt on the modules. Although this method is not expensive, human inspection may fail to detect subtle or internal defects like microcracks [20]. In addition, electrical testing is used to compare actual and expected values of efficiency based on current–voltage (I-V) curves. Although this method is effective, these tests require specialized equipment and controlled conditions. This makes them less practical for continuous real-time monitoring [22]. Various types of cameras have been used to image PV defects. For example, infrared thermal imaging cameras are used to detect thermal defects such as hotspots and are often deployed on drones for large-area inspection [9].

Electroluminescence (EL) cameras provide high-resolution images that can detect microcracks and internal defects not visible through thermal imaging [23]. Other imaging technologies include ultraviolet (UV), multispectral, hyperspectral and visible-light imaging. Overall, these imaging technologies play an important role in deep learning models for efficient defect inspection in PV systems. Several deep learning architectures have been explored to detect and classify PV defects. Chen et al. [24] proposed multispectral deep convolutional neural networks to detect defects caused by misalignment through spectral band differences. Using visible and infrared images captured by drones, Di Tommaso et al. [25] developed a YOLOv3 model to classify hotspots and thermal defects in PV panels.

A convolutional neural network (CNN) was also applied to thermal imaging data and achieved high accuracy in detecting hotspots (96.96%) but lower performance for crack detection (88%) [26]. Transfer learning models such as AlexNet show strong generalization performance within limited datasets although they rely heavily on data preprocessing [27]. Other architectures like GoogLeNet and ResNet have also shown promising results with GoogLeNet achieving 94.6% accuracy in detecting

defects from electroluminescence images and ResNet achieving 90.15% accuracy using thermal data. However, both models require large datasets and complex preprocessing which may limit practical implementation [28]. A deep convolutional neural network (DCNN) achieved excellent performance (97.62% accuracy) particularly with limited labeled data, but still required high-quality images [29].

Furthermore, hybrid models such as NASNet LSTM combine spatial feature extraction with temporal analysis and have achieved 84.75% accuracy, but require complex training and large datasets [30]. The Electroluminescence Photovoltaic (ELPV) dataset is also used in PV defect studies. It contains 2,624 grayscale solar cell images from 44 PV modules. In addition, the PVEL-AD dataset contains 36,543 near-infrared EL images with 12 defect categories and more than 40,000 annotated defect regions. In terms of PV health monitoring from EL images, Demirci et al. [31] combined multiple pretrained deep feature extractors including ResNet-50, VGG-16, VGG-19 and DarkNet-19 with classifiers such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) and Naïve Bayes (NB) [31].

The proposed approach achieved 94.52% accuracy for binary classification and 90.57% for four-class classification on the ELPV dataset. Similarly, Al-Waisy et al. [14] fused Inception-V3 and ResNet50 features with augmentation techniques such as rotation, flipping, Gaussian blur and contrast enhancement. Their model achieved 98.15% binary classification accuracy and 95.35% multiclass accuracy [14]. Wang et al. [32] proposed an integration of ResNet152 and Xception with attention mechanisms and class weighting strategies to improve minority defect classification performance. Transfer learning and lightweight architectures have also attracted attention due to computational efficiency requirements. Akram et al. [33] introduced a lightweight CNN trained from scratch which achieved 93.02% accuracy while maintaining low CPU inference time of approximately 8 ms per image [33].

Meanwhile, Al-Otum [28] proposed a lightweight multiscale CNN called LwNet together with modified ELPV categorization schemes and achieved approximately 96.2% accuracy in eight-class classification tasks [28]. Deep learning methods still face practical difficulties in PV defect classification. For example, traditional deep learning models may have low detection accuracy when dealing with complex faults of photovoltaic modules and images under different environmental conditions especially when the defect features are not obvious or the image quality is poor. In addition, existing models often rely on large datasets for training. According to Kharsa et al. [34], the mechanisms of superposition and entanglement in quantum theory make it possible to match or exceed the accuracy of classical deep learning models with fewer parameters.

2.2 Hybrid quantum–classical image classification

In previous PV EL studies, classification methods were based on the fusion of classical deep features or the coupling of a deep feature extractor with a conventional classifier. For example, Al-Waisy et al. [14] combined Inception-V3 and ResNet50 feature representations while Demirci et al. [31] coupled deep feature extraction with classical machine learning classifiers. These approaches are relevant performance baselines for EL image defect classification, but neither introduces a quantum circuit into the image feature extraction or classification pipeline.

Long et al. investigated a hybrid quantum–classical–quantum CNN using binary classification tasks drawn from MNIST, Fashion-MNIST and brain MRI images. Their experiments compared a classical CNN, a quantum-CNN model and a full model with an additional variational quantum classifier [35]. The quantum filter used a 2×2 patch and produced a $14 \times 14 \times 4$ feature map. The model also used a two-qubit variational classifier [35]. Their experiments used substantially longer training schedules, including 100 epochs for the image classification curves and varied ansatz depth

rather than fixing every model to a six-epoch budget [35]. This design is relevant because it separates the effect of quantum feature extraction from the effect of a quantum classification head.

Liu et al. [15] developed a hybrid quantum-classical convolutional framework that uses quantum-enhanced feature mapping and evaluated it using the Tetris dataset. Li et al. [16] combined parameterized quantum convolution and pooling with a classical fully connected layer on MNIST. Cheng et al. [36] further redesigned both convolutional and fully connected stages with parameterized quantum circuits and assessed binary and multiclass MNIST classification.

Hoo and Tan evaluated four structured HQCNN variants on MNIST for ten epochs with a PennyLane simulator. Their models varied the quantum topology, encoding fidelity and classical post-processing depth. The reported variants used five qubits in one configuration and seven qubits in another [37]. The study illustrates why circuit topology, encoding, qubit count, and training schedule must be reported alongside accuracy. It does not establish performance on PV EL images.

Basilewitsch et al. compared classical and quantum-classical convolutional pipelines on industrial images. Their analysis found statistically equivalent performance across classical and hybrid approaches in most settings [38]. They also used hyperparameter analysis to examine which circuit properties contributed to performance rather than treating the presence of a quantum layer as sufficient evidence of improvement [38]. Hybrid models have been tested on standard, medical and industrial images, but these studies use different image modalities and different settings. On the other hand, this study applies a hybrid quantum convolutional stage to a PV near-infrared EL classification subset.

The gap is therefore at the intersection of the two literatures. Existing hybrid QCNN studies principally use generic benchmark images while the EL-based PV studies reviewed above use classical CNN, transfer-learning or classical hybrid pipelines. Within the EL-based PV defect studies considered here, no evaluation was identified in which a quantum convolutional layer is embedded in a classical CNN to classify PV cell defects from near-infrared EL images. The present work is therefore positioned as an application specific feasibility evaluation of an existing hybrid QCNN method, benchmarked against established classical PV classifiers.

3. Methodology

3.1 Hybrid Quantum Convolutional Neural Network

This paper adopts the quantum convolutional neural network (QCNN) framework developed by Edward Farhi and Hartmut Neven [39]. In this architecture, successive quantum operations extract features while reducing the size of the input quantum state. Its structure is shown in Figure 1. In Figure 1, the key components of the QCNN can be related to those of a classical CNN. Referring to Figure 1(b), quantum convolution is performed by applying local unitary operations to neighboring qubits similar to convolutional filters in classical CNNs. These operations as represented by the U and V blocks capture local correlations within the input quantum state ρ similar to how convolution layers (C) in Figure 1(a) extract local features from an image.

Second, quantum pooling reduces the number of qubits while retaining the most significant information. This is achieved through the measurement symbols beneath the V blocks in Figure 1(b) similar to pooling layers (P) in classical CNNs. Third, the repeated application of quantum convolution and pooling operations forms the hierarchical structure shown in Figure 1(c). The hierarchy follows the structure of the Multiscale Entanglement Renormalization Ansatz (MERA). It progressively reduces the system size while enabling the model to learn global patterns from local quantum interactions similar to deeper layers in Figure 1(a). Finally, the output layer performs quantum

measurement to produce the final prediction. This is represented by the measurement after the F block in Figure 1(b) and the top measurement node in Figure 1(c).

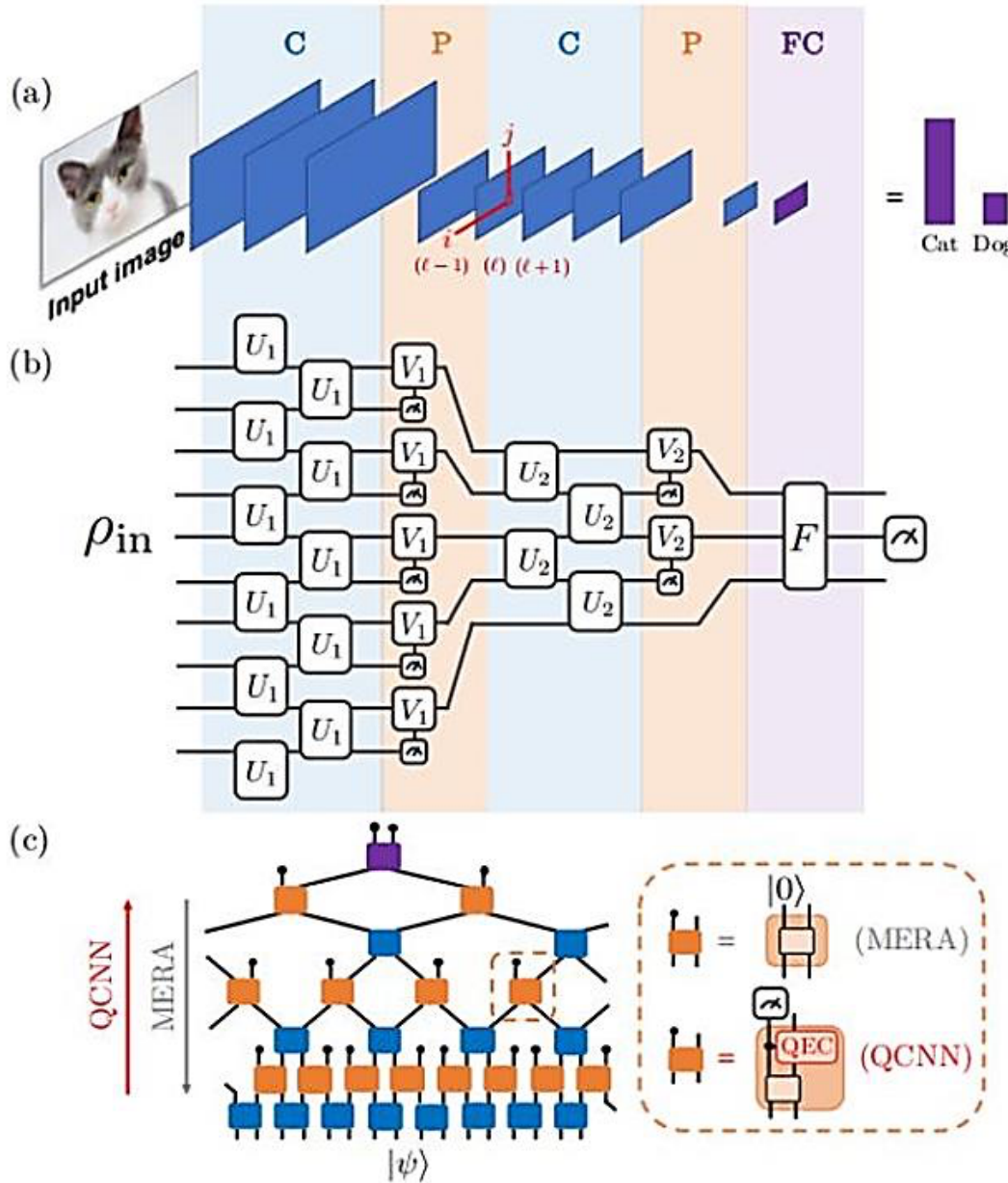


Fig. 1. QCNN architecture [39]

When compared with Figure 1(a), the QCNN can be interpreted as a quantum analogue of classical image classification where the input image is a quantum state that is processed through quantum operations and measured to generate the classification result such as “Cat” or “Dog.” Figure 1 helps explain the operation and purpose of a QCNN at the quantum level from the perspective of classical image classification. By introducing new feature learning and multitask learning strategies, QCNN can improve the robustness of the model and achieve accurate and efficient automatic detection. In the actual experiments, it was found that QCNN training required a long time per epoch because it involved quantum-circuit operations. To validate the efficacy of quantum computing in improving the classification performance of CNN-based models, a Hybrid QCNN is proposed that combines QCNN and CNN.

Figure 2 shows the proposed Hybrid QCNN structure. We modified the CNN by replacing its first convolutional layer with a quantum layer. This layer processes image patches through a quantum circuit. Due to the introduction of quantum computing, quantum convolutional layers no longer perform classical convolution operations but instead utilize quantum circuits and related quantum computations. Figure 3 illustrates the working principle of the quantum convolutional layer. First, a 2×2 block is extracted from the image, as determined by the kernel size, and each of the four values is normalized to the range $[0, \pi/2]$. If fewer than four elements are obtained, zero padding is applied to ensure that four elements are used.

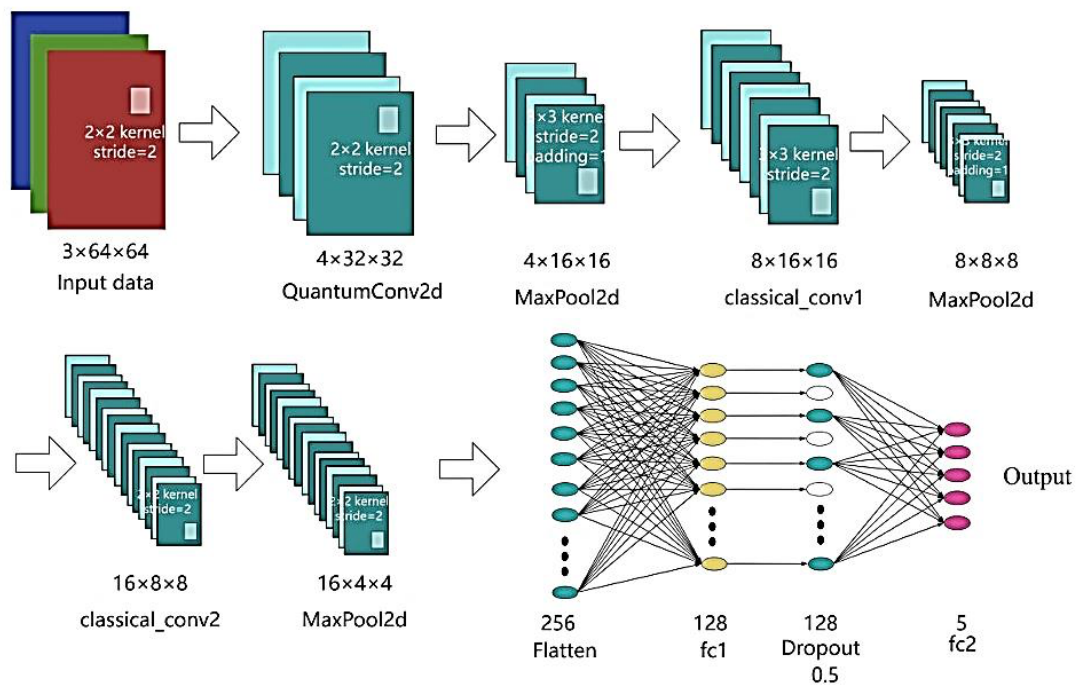


Fig. 2. Hybrid QCNN architecture

Next, quantum encoding is performed whereby the four input values are encoded into the rotation angles of four qubits using the RY rotation gate. A ring-like entanglement is then established among the qubits using four CNOT gates (represented by black dots in the figure) followed by parameterized rotations applied via additional RY gates. Subsequently, the expectation value of each qubit is computed with respect to the Pauli-Z operator and the average of these expectation values is taken as the output (eigenvalue) for that position. This process completes a single quantum convolution operation. The formula of the RY rotation gate is: $R(Y) = \begin{bmatrix} \cos Y & -\sin Y \\ \sin Y & \cos Y \end{bmatrix}$. The formula of the Pauli-Z gate is: $Z = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$. The formula for the controlled-NOT gate is: $CONT = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$. Then, the entire image is convolved using a sliding window with a step size of 2 until the quantum circuit has processed all regions, thereby generating a four-channel feature map [40].

In summary, the quantum convolutional layer was implemented using a four-qubit variational quantum circuit where each qubit corresponds to one pixel value from a 2×2 image patch. The four input values were encoded using RY angle encoding followed by one cyclic entanglement layer using CNOT gates. A single trainable RY rotation was then applied to each qubit, resulting in four trainable quantum parameters. The Pauli-Z expectation value of each qubit was measured to generate four quantum feature outputs which formed a four-channel feature map. In this study, one quantum

convolutional layer was used to replace the first convolutional stage of the classical CNN. The extracted quantum feature maps were subsequently passed to the remaining classical CNN layers, consisting of convolutional feature extraction, fully connected layers and the final five-class softmax output layer.

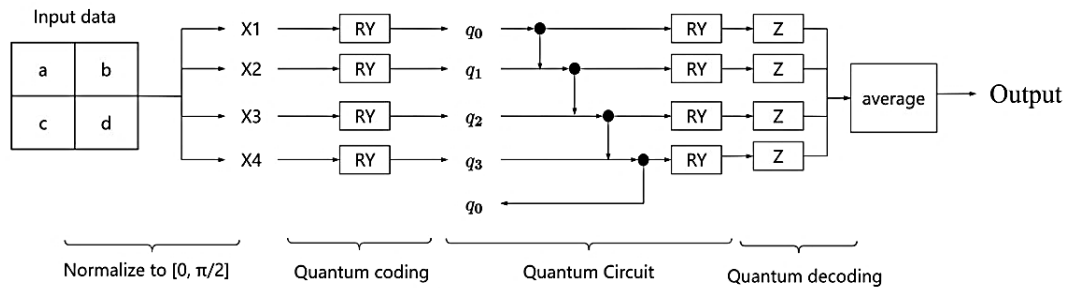


Fig. 3. Quantum convolutional layer

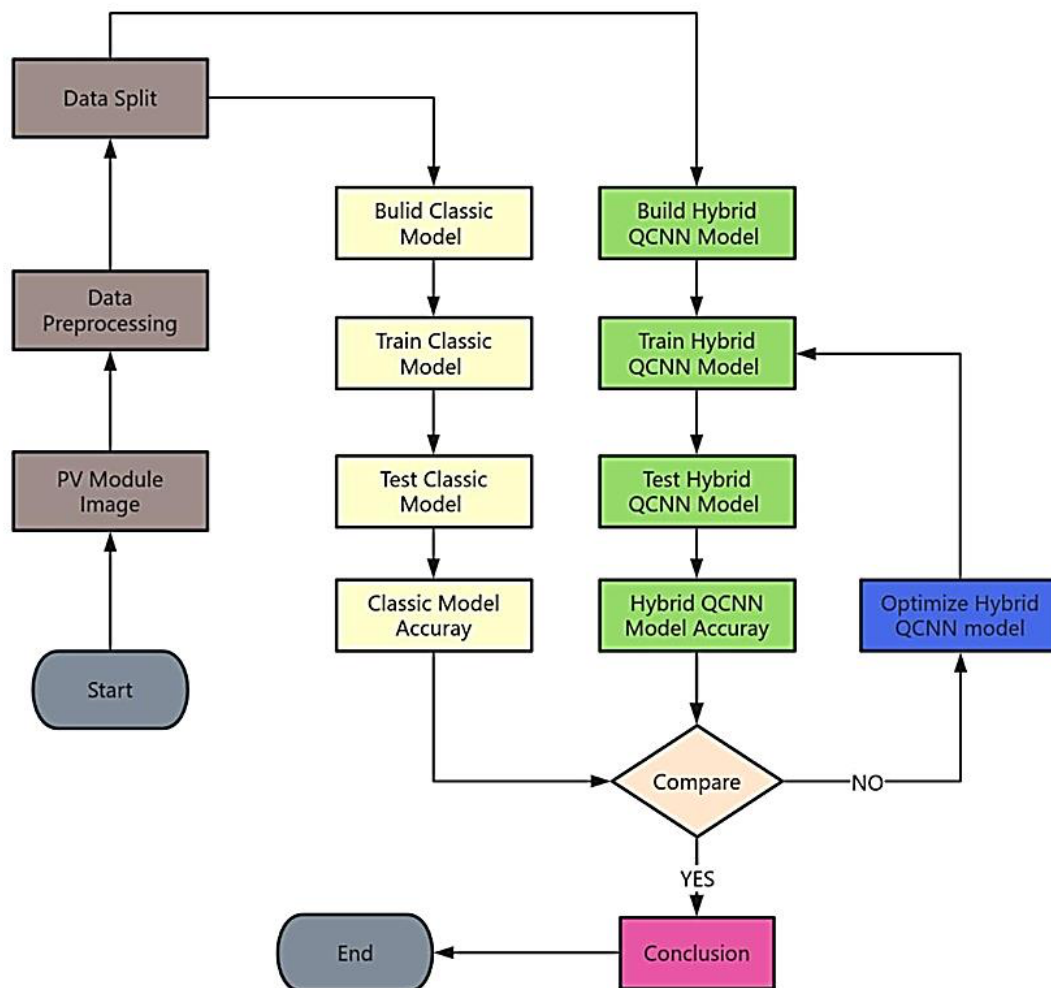


Fig. 4. Methodology flowchart

Figure 4 shows the implementation of the Hybrid QCNN feasibility study for photovoltaic module health classification. In Phase 1, PV module EL images are obtained and preprocessed. Phase 2 involves implementing several CNN deep learning models to evaluate their performance. Then, in Phase 3, the Hybrid QCNN model is established, the same data are used for simulation, and its performance is evaluated and compared with that of traditional models. Finally, in Phase 4, the Hybrid QCNN model is optimized so that its performance can reach the expected level and its feasibility for assessing the health of photovoltaic modules is evaluated. We used the PVEL-AD dataset, which was developed by Hebei University of Technology and Beihang University for photovoltaic cell defect detection [9].

The dataset consists of near-infrared (NIR) images acquired in an industrial measurement environment. It contains 36,543 near-infrared electroluminescence (EL) images, each taken from real production lines with authentic backgrounds and lighting variations. There are 12 typical defect categories and 1 normal category. For this feasibility study, a five-class subset comprising 409 images was selected. The subset was used to restrict the computational cost imposed by quantum-circuit simulation; it should not be interpreted as representing the full PVEL-AD dataset. The defect categories and corresponding image counts are shown in Table 1.

Table 1
PVEL-AD dataset

Defect Type	Number of Images
Black	100
Crack	83
Finger	109
Short Circuit	49
Thick Line	68

Figure 5 shows one randomly selected example from each category of images (Black, Cracks, Finger, Short circuit and Thick line). Since only five classes from the PVEL-AD dataset were used, the findings should be interpreted as preliminary evidence of feasibility rather than definitive proof of generalization across all PV defect categories. We used 85% of the images for training and 15% for testing, monitoring validation accuracy and loss during training. To evaluate the models, the following metrics were used:

1. Accuracy gives the proportion of samples assigned to the correct class. $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$ TP: True Positives TN: True Negatives FP: False Positives FN: False Negatives
2. An N×N confusion matrix records how samples from each of the N classes are classified, making both correct predictions and errors visible.
3. The receiver operating characteristic (ROC) curve traces the performance of a binary classifier across decision thresholds. It plots TPR on the vertical axis against FPR on the horizontal axis. The area under this curve (AUC) lies between 0 and 1; a value of 1 represents perfect discrimination in the evaluated samples. $FPR = \frac{FP}{FP+TN}$ $TPR = \frac{TP}{TP+FN}$ Additional assessments consider resource use and computational performance, which are important for practical applications. Inference time measures how long the model takes to process an input and return a prediction. Parameter count records the number of model parameters learned during training. A smaller parameter count can reduce model storage requirements, although computational efficiency and overfitting also depend on the architecture and training conditions.

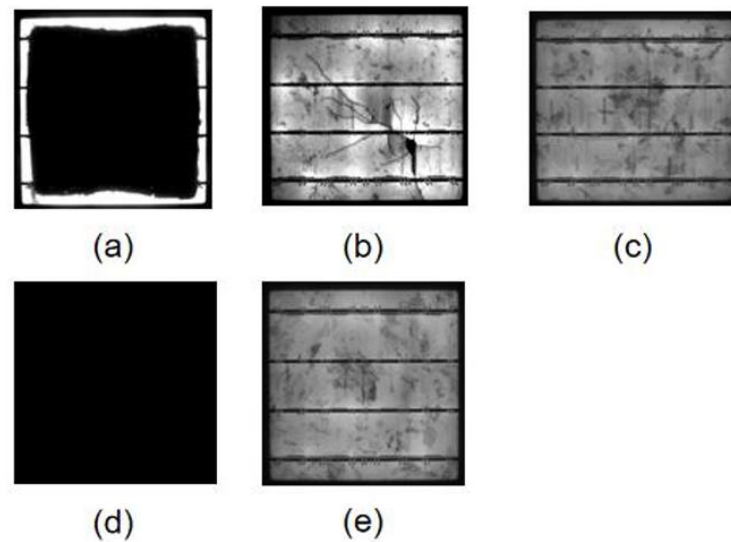


Fig. 5. Selected images from the PVEL-AD dataset: (a) Black, (b) Cracks, (c) Finger, (d) Short circuit, and (e) Thick line

The processor used in this experiment is the 13th generation Intel® Core™ i7-13650HX, with a base frequency of 2.60 GHz. The system has 24.0 GB of RAM, which provides sufficient capacity for data processing and model operation. The experiments used an NVIDIA GeForce RTX 4060 Laptop GPU with 8 GB of video memory. The software environment consisted of Windows 10/11 (64-bit) and Python 4.1.3.10. Training used the deep learning and quantum computing frameworks PyTorch 2.0 and PennyLane 0.35.

4. Results and Discussion

We compared the traditional deep-learning models with the Hybrid QCNN using accuracy, confusion matrices, inference time and parameter count. To keep the comparison consistent, every model used the same data split, preprocessing, input size, optimizer, learning rate, batch size, loss function and number of epochs. All models were trained for six epochs with Adam at a learning rate of 0.001 and cross-entropy loss. The corresponding training curves are shown in Figures 6–12.

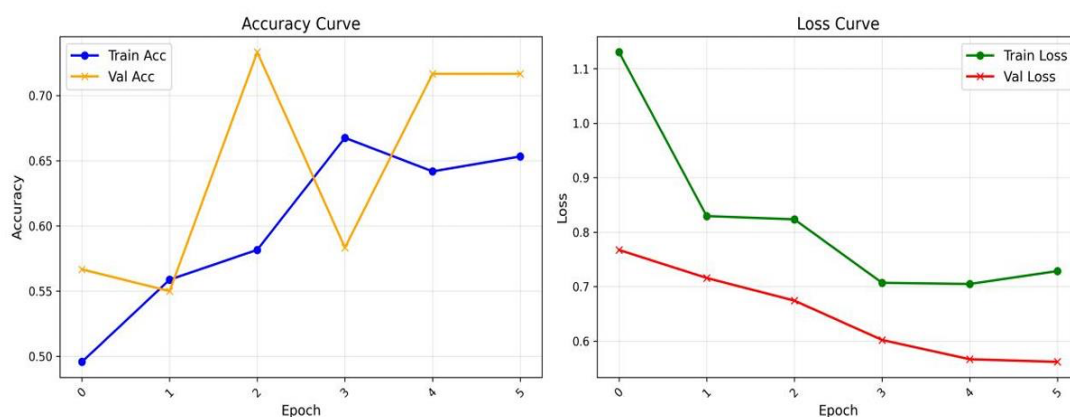


Fig. 6. CNN accuracy and loss curves (6 epochs)

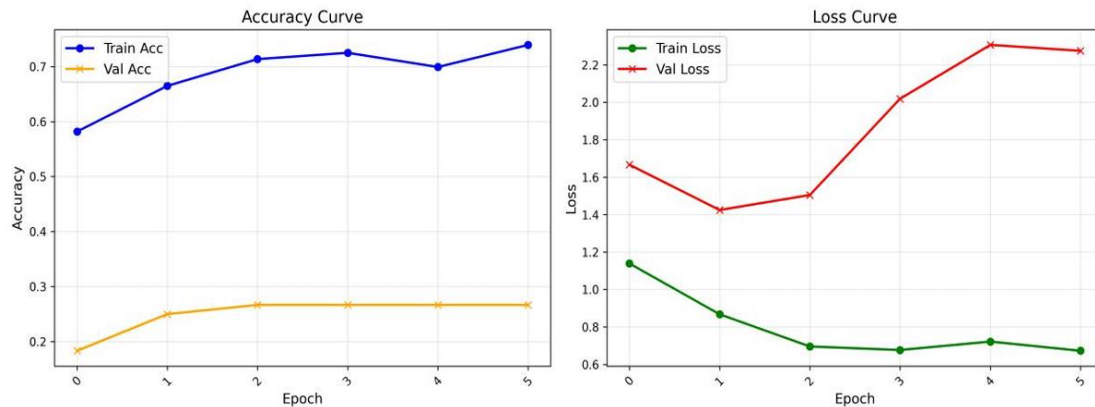


Fig. 7. DenseNet accuracy and loss curves (6 epochs)

Figures 6–12 present the training and validation accuracy as well as the training and validation loss of the conventional deep learning models trained for six epochs, including CNN, DenseNet, GoogLeNet, ResNet18 and AlexNet, as well as the Hybrid QCNN. In Figure 6, the training and validation curves of the classical CNN model are shown. The CNN model showed the most stable learning trajectory among all evaluated models and achieved approximately 71% validation accuracy with consistent loss reduction. Also, the model shows higher validation accuracy than training accuracy in several epochs. Within this 409-image, five-class experimental subset, the CNN demonstrates a good balance between learning performance and validation performance.

For DenseNet in Figure 7, the training accuracy is consistently higher than the validation accuracy. The training accuracy increases to around 70% but the validation accuracy is just around 26%, with validation loss increasing after the initial epochs, indicating overfitting. As DenseNet is a deep architecture, these findings show the limitation of DenseNet under the present six-epoch training protocol on the 409-image, five-class experimental subset. Although DenseNet is parameter efficient in principle, it can also severely overfit when data are scarce. Wan et al. [41] observed that DenseNets can experience overfitting as network depth increases. The dense connectivity multiplies the number of feature maps in deep layers which makes standard regularization less effective. This explains why DenseNet training accuracy increases while its validation accuracy stagnates and the model fails to generalize under the present six-epoch training protocol. In Figure 8, the GoogLeNet model shows a better trend than DenseNet. Both training and validation accuracy improve across the epochs and the validation accuracy reaches around 61% at the final epoch. The validation loss also decreases by the last epoch, showing effective learning from the dataset. However, the curves fluctuate especially in validation accuracy and validation loss, indicating that they have not fully stabilized within six epochs. For the ResNet model in Figure 9, training accuracy increases to more than 70% but the validation accuracy remains very low and drops at the final epoch. The validation loss is extremely high at the beginning and decreases gradually but remains higher than the training loss. This indicates severe overfitting, poor generalization and unstable learning.

The figure demonstrates critical failure patterns in the model's learning behavior under the six-epoch training protocol. Residual connections allow ResNet to train deep networks more effectively [42]. However, its potential was not fully realized under the present training protocol. With only six training epochs on the 409-image, five-class experimental subset, ResNet18's high capacity with many layers and residual skips cannot compensate for undertraining or class imbalance. In Figure 10, the AlexNet model shows moderate improvement in both training and validation accuracy. Its validation accuracy fluctuates across epochs and reaches around 43% at the final epoch. Unlike the classical CNN, AlexNet shows epoch-to-epoch fluctuations in validation accuracy.

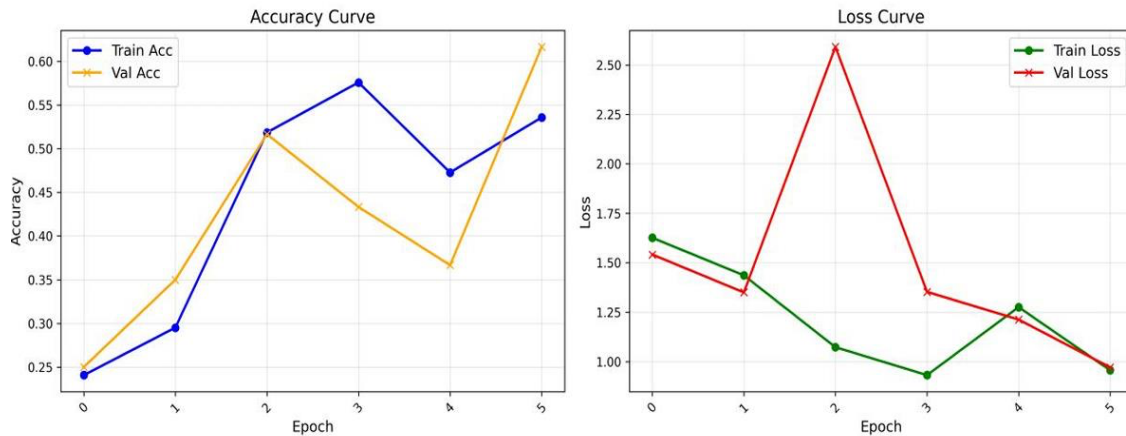


Fig. 8. GoogLeNet accuracy and loss curves (6 epochs)

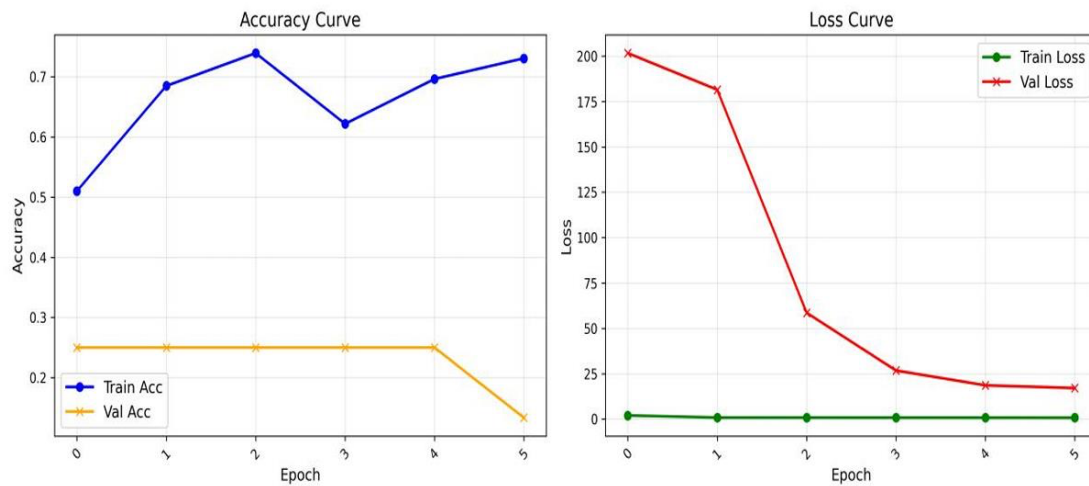


Fig. 9. ResNet accuracy and loss curves (6 epochs)

This suggests unstable validation performance. This may be caused by limited training data, insufficient epochs or the model's inability to extract strong features for this specific PV defect classification task. The AlexNet architecture, which uses approximately 60 million parameters and large 11×11 kernels, was optimized for large-scale, 1,000-class ImageNet tasks [43]. Thus, on this small EL dataset, this model experienced undertraining and overfitting. With only 6 training epochs, the model likely failed to converge on fine defect patterns. Furthermore, its receptive fields defined by 11×11 filters make it insensitive to the small EL defect features. Figure 11 shows that the CNN-LSTM model achieved reasonable but not superior performance for PV defect classification.

The training and validation accuracy increased during the six epochs with a corresponding decrease in loss. This indicates that the model was able to learn some useful features from the EL images. However, its final accuracy of 70.00% was still lower than that of the simple CNN model, which achieved 71.66%. The lower performance of CNN-LSTM can be theoretically explained by the nature of the dataset. PVEL-AD defect images are static single-frame images in which the important information is mainly spatial, such as cracks, dark regions, finger interruptions and local intensity variations. Since LSTM is designed to model temporal dependencies, it is better suited to video, time-series or sequential image data rather than single-image classification. Therefore, in this study, the LSTM component may not provide meaningful additional information beyond the CNN spatial feature extractor and instead adds unnecessary parameters and inference delay.

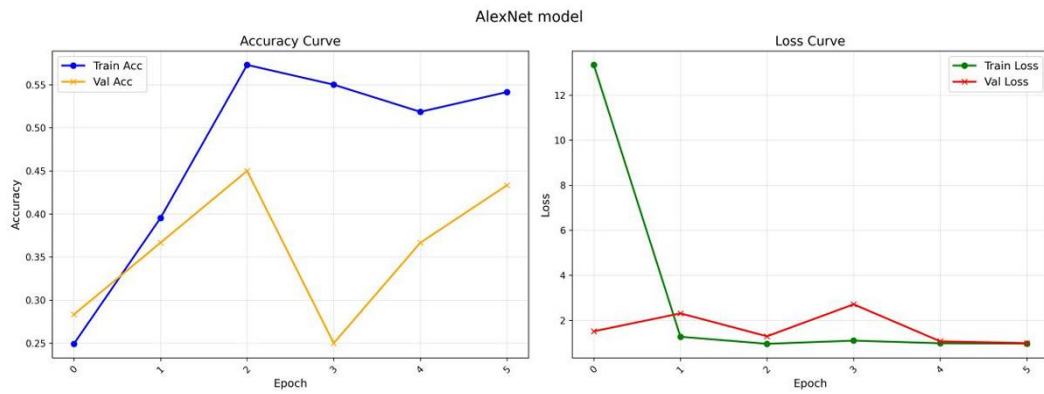


Fig. 10. AlexNet accuracy and loss curves (6 epochs)

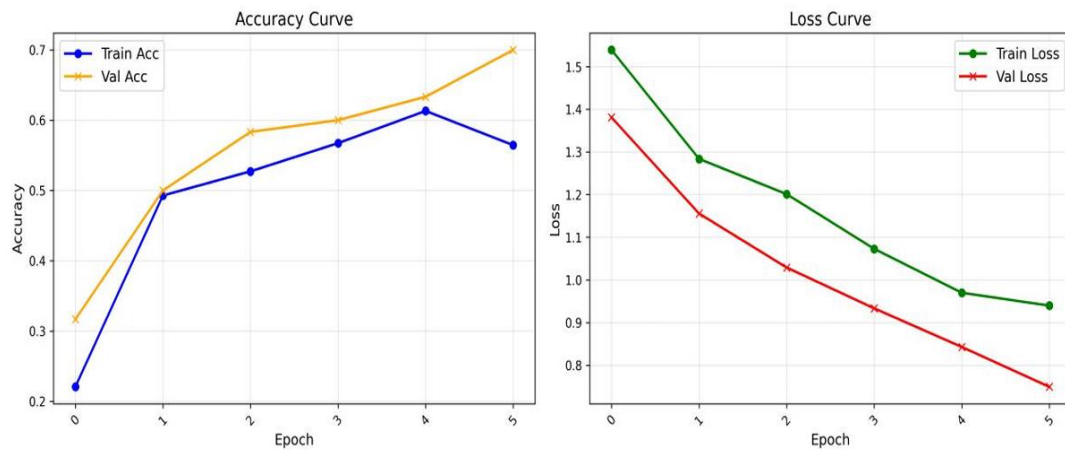


Fig. 11. CNN-LSTM accuracy and loss curves (6 epochs)

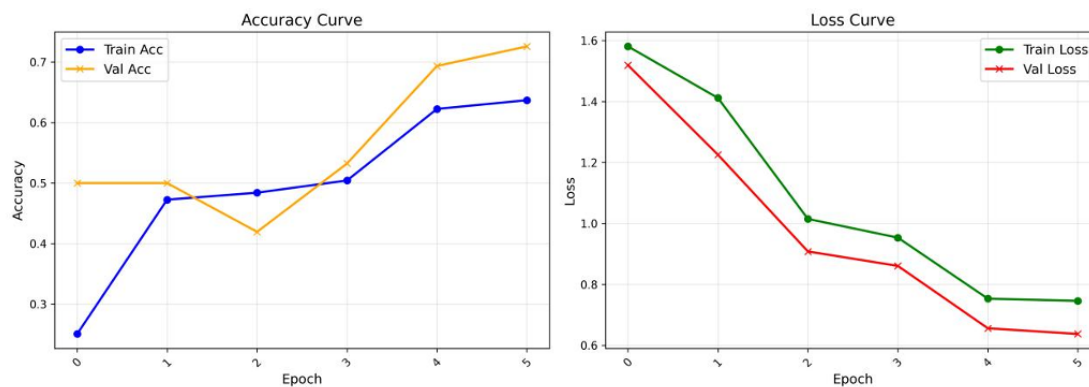


Fig. 12. Hybrid QCNN accuracy and loss curves (6 epochs)

This observation is consistent with previous studies showing that CNN-LSTM architectures are mainly beneficial when temporal sequence information is present while standalone CNNs are generally sufficient for purely spatial image classification tasks [44]. Figure 12 shows that the Hybrid QCNN has a positive learning trend over six epochs. The training accuracy increases rapidly while the validation accuracy also improves and reaches about 75.80%, which is the highest among the compared models. Both training and validation losses generally decrease. This shows that the model learns useful and more generalizable features instead of simply memorizing the training data. The good performance of the Hybrid QCNN can be explained by its quantum convolutional layer which

uses quantum encoding, entanglement, parameterized rotations and measurement to extract compact feature representations from the EL images.

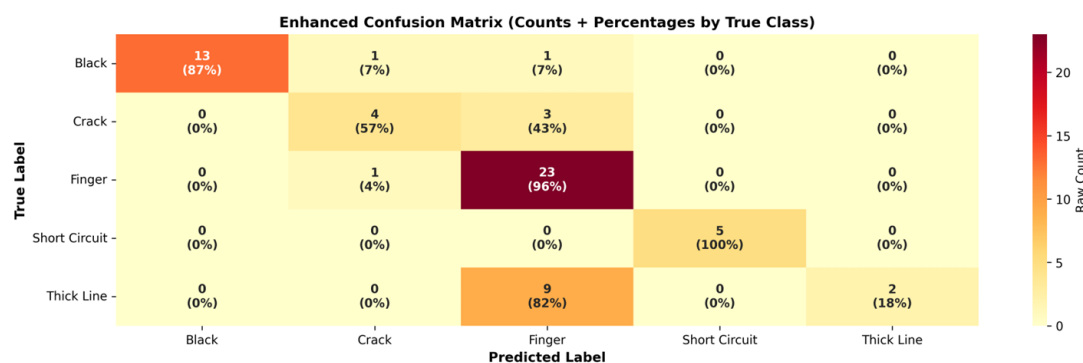


Fig. 13. Hybrid QCNN confusion matrix

Recent research has demonstrated that quantum convolutional neural networks (QCNNs) use quantum superposition and entanglement for enhanced feature extraction compared to classical approaches [45]. Furthermore, studies on hierarchical quantum architectures show that the integration of quantum convolution and entanglement structures preserves quantum correlations in data more comprehensively, leading to better classification [46]. Although the model has only 35,021 trainable parameters, it performs better than larger classical models such as AlexNet, ResNet18, DenseNet121 and GoogLeNet within 6 epochs. Research has confirmed that QCNNs achieve competitive performance on image classification tasks with significantly fewer parameters than classical counterparts [45].

Hybrid quantum-classical architectures demonstrate that models with minimal parameter counts explore broader feature spaces and capture more complex, nonlinear representations of data [47]. This indicates that the quantum-classical structure may help capture subtle defect patterns in PV images more efficiently especially when the dataset is limited. However, the main limitation of the Hybrid QCNN is its computational cost. Although it is parameter efficient, its average inference time is high at 26.2921 s mainly due to quantum circuit simulation, encoding, entanglement and measurement operations. Research on QCNN deployment confirms that while quantum circuits offer representational advantages, the simulation overhead and measurement complexity remain significant practical constraints [48].

Therefore, while the Hybrid QCNN is promising for accurate and compact PV defect classification, it is not yet suitable for real-time monitoring. Future work should focus on reducing inference time and improving quantum layer efficiency. The model comparison presented in Table 2 shows the relative performance of six conventional deep learning models and the proposed Hybrid Quantum Convolutional Neural Network (Hybrid QCNN) after six training epochs. The models were evaluated using three main indicators, namely classification accuracy, average inference time and total number of trainable parameters. Based on the results, the Hybrid QCNN achieved the highest accuracy of 75.80%, slightly outperforming the conventional CNN which achieved 71.66%.

This indicates that the hybrid quantum-classical architecture may provide a more effective feature representation for PV defect classification under the current experimental setting. The enhanced feature extraction capability through quantum superposition and entanglement can enable broader feature space exploration [47]. Importantly, the performance of quantum-based neural networks is highly dependent on the dataset, task characteristics and implementation conditions [49] particularly when trained for a limited number of epochs, as in this study. In terms of

parameter efficiency, the Hybrid QCNN appears highly compact using only 35,021 trainable parameters whereas the conventional CNN used 1,207,717 parameters. However, this apparent advantage should not be assessed based on parameter count alone.

Table 2

Performance comparison of all models under six-epoch training

Model	Accuracy	Avg. Inference Time (s)	Total Parameters
CNN	71.66%	0.0177	1,207,717
CNN-LSTM	70.00%	0.1569	4,504,331
AlexNet	43.33%	0.0180	58,303,237
ResNet18	13.33%	0.0142	11,179,077
DenseNet121	26.66%	0.1734	6,958,981
GoogLeNet	61.66%	0.0182	5,978,677
Hybrid QCNN	75.80%	26.2921	35,021

Although the Hybrid QCNN has far fewer parameters, its average inference time was 26.2921 s, which is substantially longer than the CNN inference time of only 0.0177 s. This shows that the quantum convolutional component introduces significant computational overhead, most likely due to quantum circuit simulation on classical hardware [48]. Such simulation challenges represent a critical bottleneck in quantum computing implementations where quantum circuits demand exponential computational resources. Therefore, while the Hybrid QCNN demonstrates strong parameter efficiency and promising classification accuracy, its current implementation is limited by very high inference latency. This creates a clear tradeoff between accuracy, compactness and computational practicality.

The inference time result is particularly important when considering real-world PV monitoring applications. A model with high accuracy but slow prediction speed may not be suitable for real-time or near real-time inspection systems especially when large numbers of PV cells or modules need to be processed continuously. In this context, the conventional CNN may still be more practical because it offers competitive accuracy, much faster inference and moderate model complexity. By contrast, the Hybrid QCNN is more suitable at this stage as a feasibility model that demonstrates the potential of quantum-enhanced feature extraction rather than as a fully deployable solution for real-time monitoring. Figure 13 presents the confusion matrix of the Hybrid QCNN model for five photovoltaic defect classes, namely black, crack, finger, short circuit and thick line.

The model correctly classified 47 of the 62 test samples, giving an accuracy of 75.8%. The model showed good classification for the finger, short circuit and black classes. For finger defects, it identified 23 of 24 samples correctly, corresponding to a recall of 95.8%. This indicates that the model was highly effective in detecting this defect type. Similarly, all short circuit samples were correctly classified with 5 out of 5 correct predictions. However, this might be because the short circuit class contains only a small number of test samples. Therefore, a larger and more balanced test set is required to confirm the reliability of the model for this defect category. For the black class, the model also performed well by correctly classifying 13 out of 15 samples with only two samples misclassified as crack and finger.

This suggests that the Hybrid QCNN was generally able to distinguish black defects from the other defect types. As further illustrated in Figure 14, the thick line class recorded the highest misclassification rate at 81.8%, followed by crack at 42.9%, black at 13.3% and finger at 4.2%. Meanwhile, the short circuit class recorded no misclassification. These results show that the main limitation of the Hybrid QCNN model lies in its difficulty in distinguishing thick line defects from finger defects. The confusion matrix also indicates that the model tends to overpredict the finger class. This

may be due to the morphological similarity between these defect types, particularly their linear structures. As a result, the model may have learned general line-based patterns rather than more specific discriminative features that separate finger, crack and thick line defects.

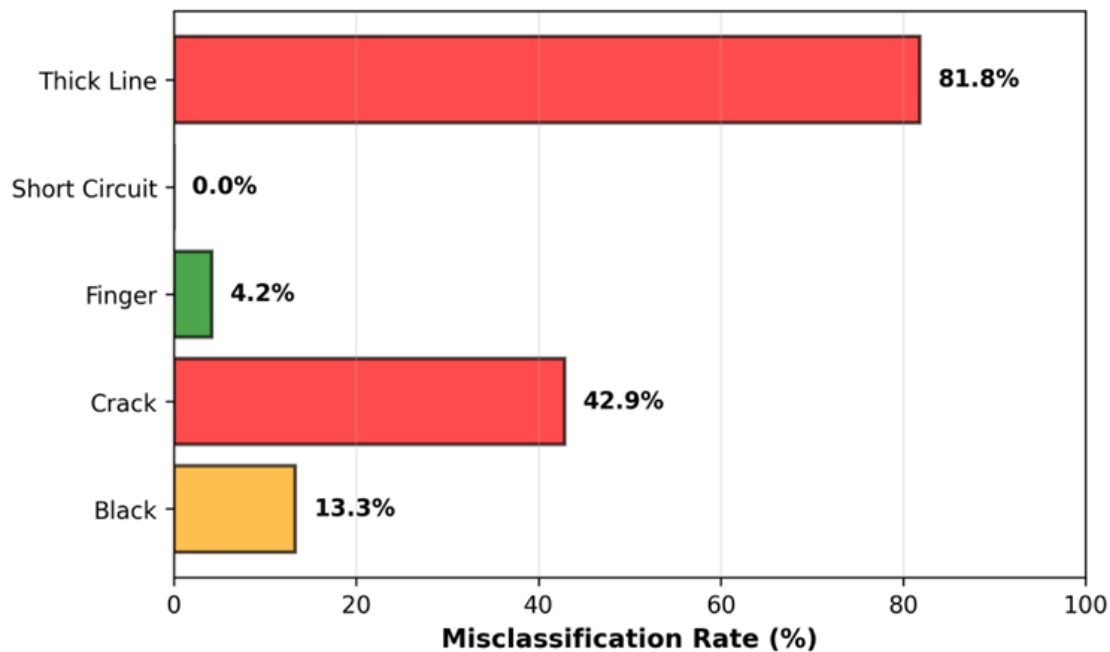


Fig. 14. Hybrid QCNN misclassification rate

In Figure 16, the ROC-AUC results indicate that the Hybrid QCNN model achieved acceptable performance although the performance varied considerably across defect classes. The short circuit class obtained the highest AUC of 1.0000, followed by black with an AUC of 0.9333. This shows that these two classes were well separated from the remaining defect categories. However, the model showed only moderate discrimination for finger and crack defects with AUC values of 0.8081 and 0.7675, respectively. The thick line class recorded the lowest AUC of 0.5909, indicating weak separability and confirming the confusion matrix observation that thick line defects were frequently misclassified as finger defects. Although the weighted average AUC of 0.8108 suggests reasonable overall performance, the large difference between the best and worst class performance highlights a limitation of the model.

This suggests that the Hybrid QCNN may have learned general line-like features rather than more distinctive characteristics to separate finger, crack and thick line defects. The implementation of the Hybrid QCNN also presents an important practical limitation in terms of computational time. As shown in Figure 12, the model was trained for only six epochs because each epoch required approximately six hours, resulting in a total training duration of about 36 hours. Although the model has only 35,021 trainable parameters and a relatively low estimated training memory requirement of 0.1336 MB, the quantum convolution operation requires repeated quantum circuit simulation. This substantially increases the computational cost. Accuracy showed an increasing trend and reached 75.81%.

This implies that further training may improve the classification performance. However, increasing the number of epochs would require a much longer training duration, making it less practical for this feasibility study. Therefore, six epochs were selected to ensure a consistent and comparable experimental setting across all evaluated models. To address computational constraints

imposed by quantum circuit simulation overhead (average inference time: 26.29 seconds per image), this feasibility study focuses on a five-class subset of the PVEL-AD dataset. However, future work will expand to all 13 categories using advanced quantum simulators or dedicated quantum processing units (QPUs) to reduce inference latency and validate generalization across all defect types. Although the achieved accuracy is acceptable for preliminary image classification, the average inference time of 26.29 seconds per image remains a major limitation. Although the Hybrid QCNN demonstrated strong parameter efficiency, its current implementation is not suitable for real-time PV monitoring due to the high inference latency caused by quantum circuit simulation on classical hardware. Future work should therefore focus on reducing quantum circuit simulation overhead, optimizing the quantum layer design and improving inference efficiency.

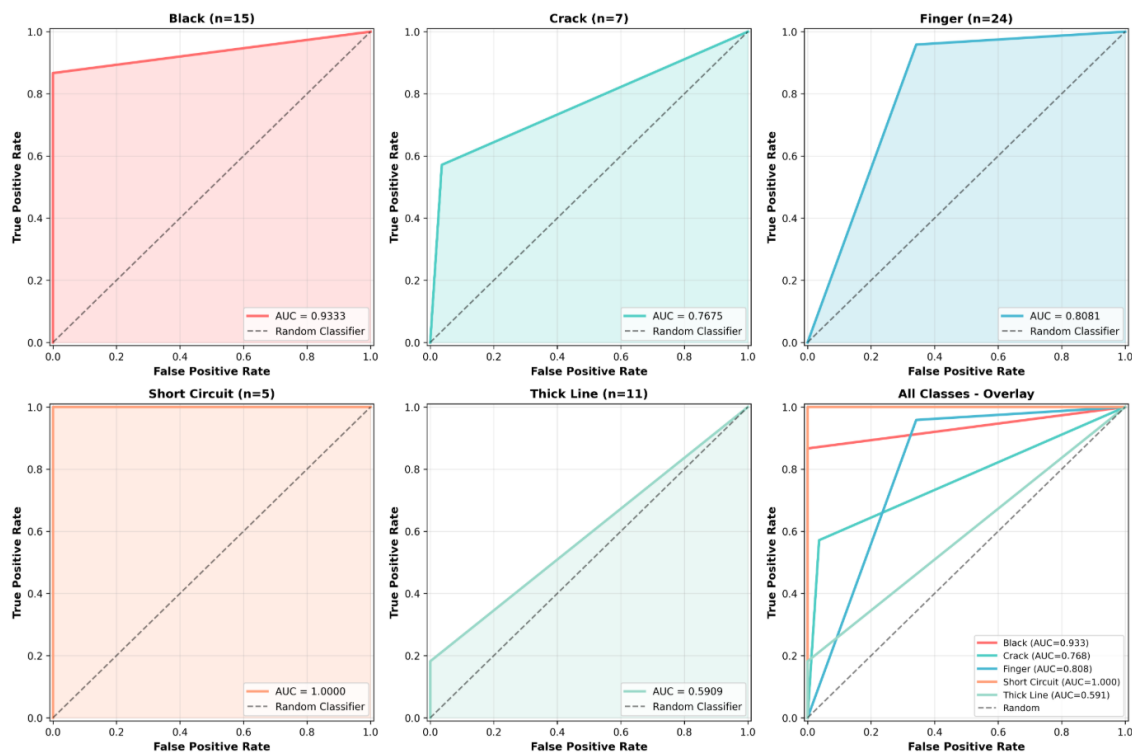


Fig. 16. Hybrid QCNN ROC curve

5. Conclusions

This study contributes an application specific feasibility evaluation of a hybrid quantum CNN for photovoltaic defect classification from near-infrared electroluminescence images. It demonstrates that a four-qubit quantum convolutional layer can be integrated with classical CNN layers and trained to classify five PV defect categories. On the 409-image subset of PVEL-AD, the Hybrid QCNN achieved 75.8% accuracy after six epochs with 35,021 trainable parameters. The contribution is evidence of the feasibility of this hybrid approach under a fixed training budget. The class-level results provide insight into the suitability and limitations of the complete hybrid model for PV EL images. The model classified black and finger defects relatively well, but frequently confused thick line defects with finger defects. The thick line AUC of 0.5909 suggests that the learned representations did not reliably distinguish these visually similar patterns. This may reflect a reliance on general line like features rather than the finer characteristics needed to separate defect types. The findings show that a small parameter count does not necessarily provide computational efficiency. Quantum-circuit simulation

required approximately six hours per epoch and 26.29 seconds per image at inference, limiting the current implementation's suitability for real-time PV inspection. Future work should include a matched classical layer ablation to isolate the contribution of quantum processing, longer training to assess convergence and evaluation on larger and more balanced datasets. More efficient simulation or quantum hardware should also be investigated, with accuracy, total computational cost and inference time evaluated together before considering practical deployment.

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Artificial Intelligence (AI) Declaration

The authors used ChatGPT (OpenAI, USA) to improve the language and clarity of this manuscript. The authors reviewed and edited all AI-assisted content and accepted full responsibility for the final version.

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